An Agent-based Travel Demand Model System for Hurricane Evacuation Simulation

Weihao Yin

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Pamela M. Murray-Tuite, Chair
Kathleen L. Hancock
Hesham A. Rakha
Kris F. Wernstedt

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ABSTRACT

This dissertation investigates the evacuees' behavior under hurricane evacuation conditions and develops an agent-based travel demand model system for hurricane evacuation simulation using these behavioral findings. The dissertation econometrically models several important evacuation decisions including evacuate-stay, accommodation type choice, evacuation destination choice, evacuation mode choice, departure time choice, and vehicle usage choice. In addition, it explicitly considers the pre-evacuation preparation activities using activity-based approach. The models are then integrated into a two-module agent-based travel demand model system.

The dissertation first develops the evacuate-stay choice model using the random-coefficient binary logit specification. It uses heterogeneous mean of the random parameter across households to capture shadow evacuation. It is found that the likelihood of evacuation for households that do not receive any evacuation notice decreases as their distance to coast increase on average. The distance sensitivity factor, or DSF, is introduced to construct the different scenarios of geographical extent of shadow evacuation.

The dissertation then conducts statistical analysis of the vehicle usage choice. It identifies the contributing factors to households' choice of the number of vehicles used for evacuation and develop predictive models of this choice that explicitly consider the constraint imposed by the number of vehicles owned by the household. This constraint is not accommodated by ordered response models. Data comes from a post-storm survey for Hurricane Ivan. The two models developed are variants of the regular Poisson

regression model: the Poisson model with exposure and right-censored Poisson regression. The right-censored Poisson model is preferred due to its inherent capabilities, better fit to the data, and superior predictive power. The multivariable model and individual variable analyses are used to investigate seven hypotheses. Households traveling longer distances or evacuating later are more likely to use fewer vehicles. Households with prior hurricane experience, greater numbers of household members between 18 and 80, and pet owners are more likely to use a greater number of vehicles. Income and distance from the coast are insignificant in the multivariable models, although their individual effects have statistically significant linear relationship. However, the Poisson based models are non-linear. The method for using the right-censored Poisson model for producing the desired share of vehicle usage is also provided for the purpose of generating individual predictions for simulation.

The dissertation then presents a descriptive analysis of and econometric models for households' pre-evacuation activities based on behavioral intention data collected for Miami Beach, Florida. The descriptive analysis shows that shopping - particularly food, gasoline, medicine, and cash withdrawal - accounts for the majority of preparation activities, highlighting the importance of maintaining a supply of these items. More than 90% of the tours are conducted by driving, emphasizing the need to incorporate pre-evacuation activity travel into simulation studies. Households perform their preparation activities early in a temporally concentrated manner and generally make the tours during daylight. Households with college graduates, larger households, and households who drive their own vehicles are more likely to engage in activities that require travel. The number of household members older than 64 has a negative impact upon engaging in out-of-home activities. An action day choice model for the first tour suggests that households are more likely to buy medicine early but are more likely to pick up friends/relatives late. Households evacuating late are more likely to conduct their activities late. Households with multiple tours tend to make their first tour early. About 10% of households chain their single activity chains with their ultimate evacuation trips. The outcomes of this paper can be used in demand generation for traffic simulations.

The dissertation finally uses the behavioral findings and develops an agent-based travel demand model system for hurricane evacuation simulation, which is capable of generating the comprehensive household activity-travel plans. The system implements econometric and statistical models that represent travel and decision-making behavior throughout the evacuation process. The system considers six typical evacuation decisions: evacuate-stay, accommodation type choice, evacuation destination choice, mode choice, vehicle usage choice and departure time choice. It explicitly captures the shadow evacuation population. In addition, the model system captures the pre-evacuation preparation activities using an activity-based approach.

A demonstration study that predicts activity-travel patterns using model parameters estimated for the Miami-Dade area is discussed. The simulation results clearly indicate the model system produced the distribution of choice patterns that is consistent with sample observations and existing literature. The model system also identifies the proportion of the shadow evacuation population and their geographical extent. About 23% of the population outside the designated evacuation zone would evacuate. The shadow evacuation demand is mainly located within 3.1 miles (5 km) of the coastline. The output demand of the model system works with agent-based traffic simulation tools and conventional trip-based simulation tools.

The agent-based travel demand model system is capable of generating activity plans that works with agent-based traffic simulation tools and conventional trip-based simulation tools. It will facilitate the hurricane evacuation management.

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CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

Hurricanes are the most costly and arguably the most frequent natural disasters in the United States (National Science Board, 2007). Facing the profound danger, many residents of the coastal areas and adjacent inland areas respond by relocating from their residences to sites they believe will be safer either under the mandatory orders of the emergency agency or due to their own judgment. This evacuation results in some of the worst traffic conditions, due to intense demand generated in a very short time (Murray-Tuite et al., 2012b).

Hurricane evacuation is a highly complex and dynamic process, which is generally modeled by using simulation-based tools (Barrett et al., 2000; Pel et al., 2012). These simulation models can be applied to obtain better insights into the effects of traffic regulations and control measures designed for improving the evacuation process (e.g., contra-flow lanes), by predicting travel times, average speeds, queue lengths, and traffic flow rates as shown in previous studies by Murray-Tuite et al. (2012a) and Wolshon et al. (2009). The first step of almost all simulation abstractions of the evacuation process requires an accurate representation of the evacuation demand, which is governed by many factors such as hurricane trajectory, hurricane warning system, and characteristics of the evacuees and their households (Baker, 1991a; Carnegie and Deka, 2010; Gladwin et al., 2001; Urbina and Wolshon, 2003). These factors contribute to households' decision-making processes during evacuation and these decision outcomes transform into evacuation demand. Though the ultimate evacuation trips constitute a large proportion of the evacuation demand, the evacuation demand also includes trips derived from the pre-evacuation preparation activities, which many evacuation simulation models fail to consider. These pre-evacuation preparation activities can span several hours or even days and often involve multiple trips between various locations (Wolshon et al., 2009). These trips generate local traffic that could affect evacuation time. It is therefore essential to capture these pre-evacuation preparation activities in the simulation model.

This dissertation econometrically models several important evacuation decisions and explicitly considers the pre-evacuation preparation activities in an integrated fashion using an agent-based modeling and simulation approach. It is essential to understand the evacuees' behavior comprehensively and thoroughly. Such understanding will lead to increased accuracy of the demand representation for simulation models and thus facilitate the development of well-justified evacuation scenarios to identify bottlenecks in the transportation system and evaluate various traffic management strategies.

The demand is often described in two distinct forms depending on the nature of the simulation model, namely origin-destination (OD) matrices for trip-based simulation models and activity plans used in agent-based simulations. The OD matrices are generally obtained from the application of the traditional four-step model (FSM) with appropriate modifications to the hurricane evacuation. While the inadequacies of the FSM are well known (e.g., see McNally and Recker (1986)), the major critique of the FSM has been the lack of valid representation of underlying travel behavior (McNally, 2007b). The motivation of the activity-based approach is precisely to explicitly recognize and address this inability of trip-based models to reflect underlying behavior. While trip-based approaches are satisfied with models that generate trips, activity-based approaches focus on what generated the activities that subsequently involve travel (McNally, 2007a). A more detailed discussion of the FSM and activity-based approach along with agent-based simulation models will be provided in Section 1.3.

The remainder of this chapter is organized as follows. Section 1.2 identifies the decisions households usually encounter throughout the evacuation process and the relationship between these different decisions. This section also provides a brief discussion as to some important issues that have been ignored by the existing literature. Section 1.3 continues the discussion of the FSM and activity-based approach and explains why agent-based simulation with activity-based approach is suitable for hurricane evacuation modeling, particularly for the modeling of pre-evacuation preparation activity travel. Section

1.4 identifies the specific research objectives, highlights of the contributions and scope of this dissertation. Section 1.5 provides an overview the structure of the dissertation.

1.2 HOUSEHOLDS' DECISION-MAKING IN THE EVACUATION PROCESS

Regardless of representation form, travel demand is derived from the desire for achieving different goals like "going to a safer place" and participating in various activities such as "shopping for medicine before evacuation". This desire is the common thread of the entire evacuation process and is characterized by a series of decisions that are generally made at the household level. The decisions generally fall into two categories, namely the evacuation decisions and pre-evacuation activity travel decisions including activity generation and scheduling. The first decision, probably the most important one, a household encounters is to determine whether to evacuate. Some households may receive mandatory evacuation orders issued by the emergency management agency while some may not. The households do not always comply with the evacuation order; as Dash and Gladwin (2007) noted, "those expected to evacuate often do not, and those who should not evacuate (at least in the estimation of emergency managers) often do" (pp. 72). Therefore, the receipt of evacuation orders is not the only factor that contributes to the evacuate-stay decision. Moreover, this suggests "shadow evacuation" often occurs. Shadow evacuation is defined as people evacuating from outside the official evacuation zone (Zeigler et al., 1981). This phenomenon was observed in many evacuations such as the Three-Mile Island nuclear disaster (e.g., see Cutter and Barnes (1982)) and Hurricane Floyd. In Hurricane Floyd in 1999, most evacuees cited evacuating because of notices from public officials. But the later survey results showed that "shadow evacuation" in low risk areas not told by officials to evacuate was high in almost every location (Sorensen and Vogt, 2006). However, most previous studies did not consider this phenomenon in the behavioral models. The literature review in the next chapter will discuss more factors that affect the evacuate-stay decision.

If a household decides to evacuate, they then face a series of decisions. They need to determine the evacuation accommodations, which generally can be a public shelter, a friend's home, family members' home or a hotel, among other choices. This decision is generally referred to as the choice of accommodation type of the evacuation destination, or simply accommodation type choice. With the accommodation type determined, they need to determine the travel mode, i.e., the evacuation mode choice. If they would rely upon their personal vehicles, they need to determine how many vehicles to use, referred to as the vehicle usage choice. While most existing studies recognize the fact that households generally use more than one vehicle for evacuation, they fail to consider the contributing factors for this decision. Chapter 4 elaborately discusses the vehicle usage choice for hurricane evacuation. A household also needs to determine the ultimate evacuation destination in terms of a city or the travel distance and direction, which are referred to as the evacuation destination choice. The household needs to decide when they will depart from their home, which is called the departure time choice.

After a household determines their departure time and destination, they usually need time to make necessary preparations for their ultimate evacuation trips. The preparation time can range from one hour, several hours or even days (Lindell et al., 2005; Wolshon et al., 2009), some of which involves travel. The purpose of these trips may include shopping, picking-up family members and friends as suggested in Liu et al. (In Press). These trips are important to the estimation of the evacuation clearance time since they may comprise a significant proportion of the traffic (Wilmot and Mei, 2004). However, these trips are generally ignored in the evacuation modeling due to the lack of relevant data (Noltenius and Ralston, 2010; Wilmot and Mei, 2004). From the perspective of an activity-based approach, the generation and scheduling of the pre-evacuation activity travel involves several dimensions of decision-making. The household needs to determine the activities they need to pursue, the travel pattern for these activities which refers to the sequence of the tours and stops. They also need to decide when to make the tour and choose the destination for each stop among the candidate destinations. A household typically needs to make the decisions aforementioned during the planning horizon defined as the duration from the start of the modeling horizon until their chosen departure time for their evacuation trip.

After a household embarks on the ultimate evacuation trip, the most important decision is the routing choice. A household's route choice is usually made based on the distance to the destination of different routes, past travel time experience, and household characteristics. Generally, the route choice can be classified into three distinct patterns based on the timing of the choice namely, pre-trip route choice, en-route route choice and hybrid route choice (Murray-Tuite et al., 2012b; Pel et al., 2012). Pre-trip route choice assumes that evacuees' determine their routes based on their experience prior to departure and never switch to another route during the entire trip. Chiu and Mirchandani (2008) argued the evacuees' tend to choose familiar routes, which is supported by Dow and Cutter (2002a) and Murray-Tuite et al. (2012b). An application of this route choice pattern for a sufficient number of iterations will result in the user equilibrium (Wardrop, 1952). Under the en-route choice assumption, evacuees would observe prevailing traffic conditions as they travel and make route choices accordingly at every possible decision point (e.g., intersection). Mitchell and Radwan (2006) applied this routing scheme in evacuation simulation using the INTEGRATION simulation package (Rakha and Van Aerde, 2004). The hybrid route choice captures the possibility that evacuees deviate from the route selected prior to departure when they perceive another route to be better due to current conditions. This route choice model is used in simulation packages such as DYNASMART (Mahamassani, 2001) and Dynus-T (Chiu et al., 2010).

1.3 THE AGENT-BASED SIMULATION AND THE ACTIVITY-BASED APPROACH

As discussed in previous sections, households typically encounter a series of related decisions. Agent-based modeling and simulation (ABMS) is a useful approach to represent this dynamic and complicated decision-making process. The ABMS methodology views systems as autonomous agents that can interact with each other and with the artificial surrounding environment (North and Macal, 2007). In ABMS, an agent is an entity with a set of attributes and behavioral characteristics. The attributes define an agent's identity and the behavioral characteristics define what an agent does (North and Macal, 2007). For instance, if a household is modeled as an agent, some typical attributes include household size, number of children, number of seniors, etc. Agents' behavioral features can include decision rules to select actions, adaptation capabilities to learn from experiences, perceptual capabilities to sense its surroundings, and optional internal mechanisms to project the possible consequences of decisions (North and Macal, 2007).

The advantages of the ABMS framework over other approaches in evacuation modeling are threefold. First, the agent is a useful abstraction capable of handling taste variation in decision-making. Second, ABMS can capture the evacuation decisions and preparation activity travel in a consistent and integrated manner. Finally, agents can interact with the external environment, such as hurricane characteristics and corresponding evacuation policies like evacuation zone designation. These advantages are further discussed in Chapter 6.

The activity plan, the output of the agent-based demand model system, describes the evacuation demand derived from evacuation-related decisions (e.g., evacuate-stay, departure time and etc.) and decisions regarding the pre-evacuation preparation activity travel. The activity plans for the pre-evacuation preparation activity travel are typically produced using the activity-based demand modeling approach. The activity-based approach is consistent with the output specifications of the activity plan in that it focuses on the patterns of activity participation instead of individual trips. The travel that is required by the activity participation can be understood and modeled only within the context of an activity participation agenda. In other words, the activity-based approach deals directly with the more fundamental desires for activities and schedules these activities according to decision entities' characteristics (McNally, 2007a). The activity-based approach is applied in Chapter 5 to understand the behavioral characteristics of the pre-evacuation activity travel. An example activity plan reads as follows. For the 5-individual household stay home from midnight till 7 AM (they are sleeping) on Tuesday, then drive to shopping at 8:20 AM and then embark on a five hour journey to their evacuation destination.

Though the activity plans assume a very distinct appearance from the OD matrices, the activity-based approach can also produce OD matrices via appropriate aggregation, which is consistent with McNally's claim (2007a) that the conventional trip-based approach is a special case of the activity-based approach.

1.4 OBJECTIVES, HIGHLIGHTS OF CONTRIBUTIONS, ASSUMPTIONS AND SCOPE OF THE DISSERTATION

The overall objective of this dissertation is to understand and capture the households' evacuation behavior with the purpose of integrating these behavioral findings into an agent-based demand model system.

Upon the identification of the possible improvements upon existing studies in Section 1.2, the highlights of the contributions this dissertation makes are as follows:

- This dissertation develops an evacuate-stay choice model that explicitly captures shadow-evacuation demand, which leads to a more realistic representation of the evacuate-stay choice.
- It also models the number of vehicles choice by statistically examining various explanatory factors, which has never been done by existing literature.
- It explicitly models pre-evacuation trips using the activity-based approach. The incorporation of the pre-evacuation trips, which has never been explicitly modeled by previous studies, enhances the accuracy of the representation of the demand patterns.
- The proposed system is the first agent-based comprehensive evacuation demand model system. It enjoys the flexibility of incorporating additional decisions and using different decision order. The proposed system can provide demand input for both trip-based and agent-based traffic simulation tools.

The scope of the dissertation corresponds to the above research tasks. Six evacuation decisions are captured, namely the evacuate-stay choice, accommodation type choice, evacuation destination decision, evacuation mode decision, vehicle usage choice and departure time choice. In this dissertation, it is assumed that the children in a household are picked up as usual and this is not considered in the picking-up activity later analyzed in Chapter 5 for the pre-evacuation activity travel. Households may perform tours in addition to the ones analyzed in this dissertation to follow their daily routines. The tours reported might be considered as the additional tours made for evacuation preparations. All the pre-evacuation activity travel decisions related to these tours will be included in the research scope while the specifications of the model components depend on the available survey data.

1.5 ORGANIZATION OF THE DISSERTATION

The remainder of the dissertation contains six chapters. Chapter 2 provides the review of the literature on household evacuation decisions and a discussion of the gaps. The studies about evacuation due to events other than hurricane are also included for certain decisions. Chapters 3 to 6 are organized according to the two categories of households' decisions, namely evacuation decisions and pre-evacuation activity travel decisions. Chapter 3 presents the econometric formulation and estimation results of the evacuate-stay choice model. Chapter 4 provides a paper entitled "A Statistical Analysis of the Number of Household Vehicles Used for Hurricane Ivan Evacuation", which has been accepted for presentation in the 93rd Annual Meeting of the Transportation Research Board. Chapter 5 provides a paper entitled "Pre-Evacuation Activities for Hurricane Evacuation: An Analysis of Behavioral Intentions from Miami Beach, Florida", which serves as the behavioral foundation for the pre-evacuation activity travel decisions. This paper has also been accepted for presentation in the 93rd Annual Meeting of the Transportation Research Board. Chapter 6 presents a paper entitled "An Agent-based Travel Demand Model System for Hurricane Evacuation Simulation". It presents the behavioral models for evacuation decisions including accommodation type choice, evacuation destination choice, evacuation mode choice and evacuation departure time choice. It also identifies the interdependence between all six evacuation decisions and sketches the simulation framework that uses the behavioral models and findings derived in Chapters 3 to 5 for generating activity plans. This paper has been presented at the Conference of Agent-based Modeling and Simulation in October, 2013. Chapter 7 summarizes and concludes the dissertation by identifying the major contributions.

CHAPTER 2 LITERATURE REVIEW

Evacuation modeling is a broad and very active research field. A comprehensive discussion of the topic of evacuation modeling is beyond the scope of this chapter. Several papers provide relatively comprehensive literature review for different branches of the evacuation modeling. The review paper by Pel et al. (2012) provides an overview of the behavioral models used in trip-based simulation models from the perspective of the conventional four-step model. They focused on how travelers' decisions are predicted through trip-based simulation regarding the choice to evacuate, departure time choice, destination choice, and route choice. They supported the modeling of departure time choice in a disaggregate fashion as in this dissertation instead of the use of departure curve and argued in favor of hybrid route choice models. Murray-Tuite and Wolshon (2013b) surveyed research, model development and practice in highway-based evacuation. Their review included modeling of evacuation travel demand, distribution and assignment of evacuation demand to regional road networks to reach destinations, assignment of evacuees to various modes of transportation, and evaluation of alternative management strategies to increase capacity of evacuation networks or manage demand. They also highlighted some special considerations such as hospitals and logistical difficulties.

The subsequent sections discuss the previous research efforts that are closely related to this dissertation. Specifically, the literature review is organized according to the different decisions identified in the previous chapter. First, the studies on evacuate-stay decision will be discussed in Section 2.1 and then Section 2.2 will survey the researches on accommodation type choice, evacuation destination choice and departure time choice. The literature on vehicle usage choice will be reviewed in Chapter 4 and that on pre-evacuation activity travel is discussed in Chapter 5. Chapter 6 will discuss some agent-based simulation applications in the literature. Section 2.3 provides concluding remarks for the chapter by highlighting some of the gaps in the literature that are addressed in this dissertation.

2.1 EVACUATE-STAY DECISIONS

(Sections 2.1.1 and 2.1.2 are taken verbatim from the paper by Yin et al. (2012a) and is written by Dr. Pamela Murray-Tuite.)

A large body of literature is devoted to identifying factors associated with the decision to evacuate/ stay when a hurricane threatens an area. The studies typically involve conducting a survey of residents for their anticipated behavior to a hypothetical hurricane scenario or their revealed behavior after a real hurricane has struck. The goals of these studies are usually to identify the factors that are prevalent or statistically significant to predicting the evacuate/stay outcome. From the social sciences perspective, the study may end at that point, while studies involving transportation modeling may then take those factors and models and apply them to the population to generate estimates of the total amount of evacuees. The review will start with the common influential factors whose effects were investigated in the previous studies. Section 2.1.2 will provide discussion as to what this dissertation considers as an improvement upon the previous research efforts.

2.1.1 Common Influential Factors

The most common reason for evacuating is that the individuals/households do not feel safe remaining in their homes (Arlikatti et al., 2006; Baker, 1979, 1991a; Bateman and Edwards, 2002; Fitzpatrick and Mileti, 1991; Peacock et al., 2005). The perception of being at risk may be directly captured by a survey question but is difficult to extend to the population, leading researchers to capture measures hypothesized to relate to this perception, such as those shown in Table 2.1.

Table 2.1 Factors Tied to Feeling Unsafe

Factor	Effect on Likelihood of Evacuating	Sources
Receiving a warning	Increases	(Baker, 1979, 1991a; Gladwin and Peacock, 1997; Hasan et al., 2011; Lindell et al., 2005; Zhang et al., 2007)
Distance to the hurricane (closer)	Increases	(Carnegie and Deka, 2010)
Storm intensity	Increases	(Whitehead, 2000; Zhang et al., 2007)
Living in a mobile home	Increases	(Baker, 1991a; Hasan et al., 2011; Solis et al., 2010; Whitehead, 2000; Wilmot and Mei, 2004)
Living in a low-lying area	Increases	(Baker, 1991a; Solis et al., 2010; Whitehead et al., 2000)
Frequent experience	Decreases	(Anderson, 1968)
Previous experience	Insignificant	(Arlikatti et al., 2006; Dow and Cutter, 1998)
Previously experienced damage	Increases	(Peacock et al., 2005; Riad et al., 1999)
Previously evacuated	Increases	(Murray-Tuite et al., 2012b; Riad et al., 1999)
Duration of residence (longer)	Decreases	(Gladwin and Peacock, 1997)

As shown in Table 2.1, many of the factors have the intuitive effect. Official evacuation orders (issued and received) alert the public to the threat and increase the likelihood of evacuation. Proximity to the hurricane intensifies the threat and also increases the chances of being directly impacted, which encourages evacuation, as does greater storm intensity. Mobile homes are more vulnerable to wind damage while residences in low-lying areas are more vulnerable to storm surge and flooding, thus, these residents are more likely to evacuate.

The effects of experience can be mixed (Lindell and Perry, 2000) and can depend on the type of experience queried. Frequent experience has been found to decrease the likelihood of evacuating (e.g. (Anderson, 1968)) due to the development of a “disaster culture”. This culture could also be associated with living in the same area for a longer duration. Previous experience on its own often (but not always) shows insignificant effects on the decision to evacuate/stay, suggesting that respondents are not likely to consider officials to "cry wolf" - issue an evacuation order when it is not needed (Dow and Cutter, 1998). However, if the home was previously damaged, the likelihood of evacuating increases as the previous impacts increase the risk perception. Finally, if households previously evacuated, they are likely to evacuate again in the future (Murray-Tuite et al., 2012a; Riad et al., 1999) perhaps due to inherent risk perceptions.

Some of the inherent perceptions of risk and hazards may be tied to socio-demographic and economic factors, such as those shown in Table 2.2, due to access to resources and social power (Peacock et al., 2005). Social power is often tied to being male and white (Peacock et al., 2005), thus women and minorities may inherently feel more threatened and have higher likelihoods of evacuating. However, race is often correlated with income; greater income implies greater access to resources needed for evacuation.

Table 2.2 Socio-Demographic and Economic Factors Associated with the Evacuate/Stay Decision

Factor	Effect on Likelihood of Evacuating	Sources
Elderly headed households/ presence of elderly	Decreases	(Dash and Gladwin, 2007; Gladwin and Peacock, 1997)
Age (older)	Decreases	(Lindell et al., 2005)
Gender (female)	Increases	(Bateman and Edwards, 2002; Lindell et al., 2005; Peacock et al., 2005; Riad et al., 1999)
Children in the household	Increases	(Dash and Gladwin, 2007; Gladwin and Peacock, 1997)
Children in the household	Insignificant	(Baker, 1991a; Riad et al., 1999)
Race/Ethnicity (Caucasian)	Increases	(Gladwin and Peacock, 1997; Riad et al., 1999)
Race/Ethnicity (Caucasian)	Insignificant	(Bateman and Edwards, 2002)
Race/Ethnicity (Latino)	Increases	(Riad et al., 1999)
Income (higher)	Increases	(Elliott and Pais, 2006; Gladwin and Peacock, 1997; Hasan et al., 2011)
Single adult household	Increases	(Riad et al., 1999)
Presence of pets in the household	Insignificant	(Baker, 1991a)
Presence of pets in the household	Decreases	(Solis et al., 2010; Whitehead, 2000)
Work obligations	Decreases	(Baker, 1991a)

Other factors reflect logistical challenges. For instance, older individuals may have medical or mobility challenges that make it difficult for them to evacuate. The presence of children has somewhat mixed effects since there is a desire to protect them (increasing the likelihood of evacuation) but larger families may face logistical challenges. Single adult households, on the other hand, are more likely to evacuate as they often do not face such challenges. Pets may either be insignificant or decrease the likelihood of evacuating due to the difficulty in finding a destination that will accept them or in travelling with them. Finally, work obligations naturally make individuals less likely to evacuate.

2.1.2 Discussion

The factors investigated in this dissertation largely draw from the factors identified in the previous literature. This dissertation distinguishes itself from previous ones in that the shadow evacuation phenomenon that discussed in Chapter 1 is considered explicitly.

2.2 ACCOMMODATION TYPE, DESTINATION CHOICE, AND DEPARTURE TIME

The review is organized into three sub-sections. Section 2.2.1 reviews the studies about accommodation type choices, followed by destination choice including travel distance and direction in Section 2.2.2. The last sub-section surveys the researches about departure time choice.

2.2.1 Accommodation Type Choice

The accommodation type at the destination city/town received repeated attention from behavioral researchers and transportation engineers (Lindell and Prater, 2007b; Mesa-Arango et al., 2012). The homes of friends and relatives are considered to be the most preferred accommodation type, followed by hotels. Mei (2002) and Modali (2005) reported percentage ranges of the accommodation type choice in various surveys. Specifically, 55%~69% of the respondents chose friends' or relatives' house, 13%~26% hotels and 3%~12% public shelters. Similarly, Sorensen (2000) indicated that shelter use averages about 15% among the evacuees.

Econometric methods were used to identify the influential factors that contribute to the accommodation type choice pattern. Murray-Tuite et al. (2012b) suggested that variables influencing the choice include hazard severity, income, size of the evacuation, type of emergency, time of the evacuation, age, and ethnicity (Mileti et al., 1992). Whitehead et al. (2000) reported that households are more likely to choose the motel/hotel destination if they have higher incomes although the magnitude of the effect is small. For each increase of $10,000 in income, the probability of choosing a motel/hotel increases by only 2%. Respondents who live in mobile homes, who perceive medium to high flood risk, who have pets, who are white and with more education are less likely to choose a motel/hotel, compared to staying with friends or family (or other). Brodie et al. (2006) made similar observations by reporting that people with higher income and education level are more likely to evacuate to hotels while people with less financial resources tend to evacuate to shelters based on the revealed-preference survey on Katrina evacuees. A later study (Carnegie and Deka, 2010) supported this finding by relating the socio-economic and demographic characteristics to evacuation accommodation type choice using a stated-preference survey. Similarly, Mesa-Arango et al. (2012) constructed a nested logit model and found that the variables influencing the accommodation type choice include hurricane position at evacuation time, household geographic location, race, income, preparation time, changes in evacuation plans, previous experiences with major hurricanes, household members working during the evacuation, and evacuation notices.

2.2.2 Destination Choice

Though the travel distance is generally recognized as an important factor for destination type choice, studies of the destination choice, i.e. travel distance and direction, are quite limited. Southworth (1991) concluded that evacuees' destination choice displayed the following characteristics: (1) They choose the closest destination (in terms of distance or travel time) beyond the at-risk area; (2) They head for pre-specified destinations according to an established evacuation plan; (3) They display some degree of dispersion in their selection of destinations, depending on factors such as the location of friends and relatives, characteristics of the hazard, and the traffic conditions on the network.

Echoing the first category of destination choice, Barrett et al. (2000) stated the destination choice was affected by the perceived minimal travel cost without identifying specific factors. Murray-Tuite et al. (2012b) studied the tendency of repeated choice in the travel distance for hurricanes Ivan and Katrina only vaguely by discerning county/out-of-county destinations.

For the purpose of modeling hurricane evacuation, many previous studies modified the techniques that are generally used for regular transportation planning like gravity models. Wilmot et al. (2006) compared the ability of standard trip distribution models, namely the Gravity Model and Intervening Opportunity Model (IOM), to reproduce the observed evacuation trips at the county level using data collected from South Carolina following Hurricane Floyd. Later, Cheng (2007) proposed a scheme for calibrating the friction factor used in the gravity model to incorporate the characteristics of the different destination zones. Cheng et al. (2008) applied this adjusted friction factor together with the gravity model to estimate the trip distribution for hurricane evacuation. They later integrated the gravity-based trip distribution model with trip generation to obtain the dynamic origin-destination matrices that described the aggregate trip-based travel distance and direction. Cheng and his colleagues reported that their models reproduced the observed traffic volumes at major routes with the traffic assignment accomplished by TransCAD and later their destination choice model was used in a simulation study of the Hurricane Katrina for the city of New Orleans (Wolshon et al., 2009). However, they reported that traffic volumes on certain roads did not match well to the observed ones.

Recognizing the inherently different characteristics of each household, Huang (2011) applied the Geographically Weighted Regression model to predict the travel distance and identified income and number of children as influential factors.

2.2.3 Departure Time Choice

(This sub-section is taken verbatim from the paper by Yin et al. (2012b) and is written by Weihao Yin)

Most of the previous studies related to departure time focused on developing aggregate empirical distributions of the departure time, which describes the rate of vehicles' entry into the emergency planning network. This distribution, or response curve, explicitly offers the percentage of departures in each time interval of the planning horizon (Pel et al., 2012). These studies assumed a variety of shapes for the departure time distributions. A widely-accepted distribution is the sigmoid curve which is similar to the cumulative normal distribution (Radwan et al., 1985; Yazici and Ozbay, 2008). The sigmoid curve, commonly used for hurricane evacuation modeling (e.g., (Wolshon et al., 2009)), is characterized by two parameters, namely the response rate and half loading time. The response rate sets the slope of the curve and low values for this parameter lead to a more uniform departure profile (Pel et al., 2012). The half loading time dictates the time at which half of the total evacuees depart. These two parameters need to be calibrated to achieve realistic representation of the departure behavior. Other notable examples in different application scenarios include the instantaneous departure in short-notice evacuation (Chiu and Mirchandani, 2008), uniform distribution (Liu et al., 2006) and Weibull distribution (Lindell, 2008) in hurricane evacuation, Rayleigh distribution (Tweedie et al., 1986) and exponential distribution (Hobeika et al., 1994) in nuclear disaster, Poisson distribution in wildfire evacuation (Cova and Johnson, 2002), and piece-wise linear curve in flooding (Southworth and Chin, 1987).

A few studies investigated the effects of various household and/or personal characteristics on the evacuation timing behavior. Sorensen (1991) made one of the earliest attempts to explain evacuation timing behavior by using path analysis for an evacuation in response to the hazardous chemical incident. Factors considered included three socio-demographic characteristics, namely age, household size and residence type. The analysis found that neither age nor family size influenced the evacuation timing behavior. The residence type variable was found to have statistically significant but weak impact upon the timing of warning receipt and subsequently the evacuation timing. Face-to-face warning dissemination was found to decrease the mobilization time before evacuation. A later study (Barrett et al., 2000) mentioned the possible effect of different covariates such as productivity, comfort, and perceived safety upon the departure timing choice but did not investigate these factors. They also recognized the possible connection between the departure time choice and destination choice. Lindell et al. (2002) highlighted the regional difference in the departure timing choice attributed to risk levels and traffic conditions.

In addition to the studies that examined the departure time choice alone, other studies considered the departure time choice together with other dimensions of the evacuation decision-making process. A notable study by Fu and Wilmot (2004) developed a sequential logit choice model, where they assumed that each household examined the surrounding conditions when a hurricane approaches. The model simultaneously considered evacuate/stay and departure timing decisions with dynamic hurricane characteristics, such as speed and household's distance to the hurricane track. Other factors included the residence type and evacuation warning receipt. Fu and Wilmot (2006) later adopted a hazard-based modeling approach to understand decisions of whether to evacuate or not and when to evacuate as a joint model. They found that a mandatory evacuation order shortened the duration until evacuation and wind speed did the same. Later, Wilmot and his colleagues adopted the theory of risk attitude in economics to jointly model the evacuate/stay decision and departure time (Dixit et al., 2012). In addition, they compared the sequential-logit approach to the nested logit approach for the evacuate/stay decision and departure time (Gudishala and Wilmot, 2012b). Their studies investigated the dynamic aspect of the decision-making process by incorporating time-dependent covariates. Factors including length of time spent in a region, evacuation warning type, and the presence of children were found to affect the evacuation decisions. Echoing these findings, the households that depart late, considered the "evacuation tail" (Wolshon et al., 2010), were found to need disproportionally longer pre-evacuation preparation time. Recently, Hasan et al. (2013a) adopted a hazard-based model with random parameters to capture the possible heterogeneity among the evacuation population. They found that the variables related to household location, destination characteristics, socio-economic characteristics, and evacuation notice were key determinants of the departure time. A summary of influential factors for departure time choice is provided in Table 2.3.

Table 2.3 Summary of Influential Factors for Departure Time Choice

Factor	**Effect on Likelihood of an Early Evacuation**	**Sources**
Socio-Demographic Characteristics		
Age	Not significant	(Sorenson, 1991)
Presence of Children	Increase	(Hasan et al., 2011a), (Huang, 2011)[a]
Presence of Senior Citizens	Not significant	(Sorenson, 1991)
Household Size	Not significant	(Sorenson, 1991)
Single Family Home	Increase	(Sorenson, 1991)
Mobile Home	Decrease	(Hasan et al., 2011a)
Residential Region	Mixed	(Lindell et al., 2002)
Low Income	Decrease	(Hasan et al., 2011a), (Gudishala and Wilmot, 2012), (Huang, 2011)[a]
High Education Level	Decrease	(Hasan et al., 2011a)
Evacuation-related Characteristics		
Mandatory Evacuation Order	Increase	(Fu and Wilmot, 2004; Hasan et al., 2011a), (Gudishala and Wilmot, 2012)
Evacuation to a Shelter	Decrease	(Hasan et al., 2011a)
Long Evacuation Preparation Time	Decrease	(Hasan et al., 2011a; Wolshon et al., 2010)
Storm Characteristics		
Small Hurricane Distance	Increase	(Fu and Wilmot, 2004, 2006)
High Hurricane Speed	Increase	(Fu and Wilmot, 2004, 2006)
[a] The study that identified the corresponding factor as influential one for evacuation distance		

2.2.4 Discussion

While mathematically simple, the response curve approaches are typically used for short evacuation (e.g., several hours) (Fu and Wilmot, 2006) and do not allow the incorporation of the socio-demographic characteristics of the evacuees (Pel et al., 2012). In addition, aggregate response curves sometimes fail to reproduce the multiple-S shape of the evacuation departures observed in many hurricane evacuations. Precisely due to these reasons, this dissertation adopts the disaggregate approach to model the households' departure time choice directly.

2.3 SUMMARY

To summarize, a large body of previous studies has focused on evacuation behaviors and provided rich and valuable contributions to the field. However, there are still some gaps that need to be filled for the decisions reviewed in this chapter. The dissertation is motivated to capture the shadow-evacuation demand. In addition, this dissertation adopts a disaggregate approach to model the households' departure time choice and integrate this choice with other evacuation decisions and pre-evacuation activity travel decisions.

CHAPTER 3 THE ECONOMETRIC FORMULATION AND ESTIMATION RESULTS OF THE EVACUATE-STAY CHOICE MODEL

This chapter presents the econometric formulation and empirical estimation results of the evacuate-stay choice. The evacuate-stay decision, probably the most important one for people affected by a hurricane, has been studied extensively by both social scientist and transportation researchers. Many factors are involved in the decision to evacuate (Gladwin et al., 2001). These factors include not only emergency management practices (e.g., evacuation warning) but household socioeconomic and demographic characteristics (Murray-Tuite and Wolshon, 2013b). As mentioned in Chapter 1, households may or may not comply to evacuation orders issued by the emergency management agency, which results in the "shadow evacuation" phenomenon. This stochastic component in the decision-making process is captured by the specification of a random-parameter binary logit model. More specifically, information on households' receipt of evacuation recommendations and their socioeconomic characteristics are used to develop a better understanding of household evacuation behavior.

This chapter is organized as follows. Section 3.1 presents the econometric formulation, followed by the presentation and discussion of the results of descriptive analysis of the Hurricane Ivan data and the empirical estimation results in Section 3.2. Section 3.3 introduces the distance sensitivity factor that can be used to construct scenarios with different geographical extent of shadow evacuation. Section 3.4 summarizes the major findings in this chapter.

3.1 THE MATHEMATICAL FORMULATION OF THE MIXED LOGIT MODEL

The dichotomous outcome of the evacuate-stay decision is well captured by the binary logit model as discussed in Hasan et al. (2011) and Yin et al. (2012a)~~.~~(~~-~~See Section 2.1 of Chapter 2 for a comprehensive review.) Recognizing the fact that the shadow evacuation population generally resides outside of the designated evacuation zones and usually do not receive any evacuation notice, their evacuate-stay decisions typically depend on their perceived risk. The perceived risk generally varies from one household to another. This inherent taste variation, as suggested by Train (2002), can be captured using a random coefficient for those households who do not receive any evacuation notice. In addition, households who live in areas far from the coast should typically perceive less risk than those who live close to the coast. To account for this parameter heterogeneity due to different distance to the coast in the underlying population, the random coefficient can be related to the household's distance to coast.

The binary logit model with random parameters is usually referred to as the mixed logit model, which here takes the random coefficient interpretation. Some parameters associated with the covariates are not deterministic but random variables whose values follow certain probability distributions. A particular covariate can exhibit heterogeneous effect in the underlying population. When the evacuate-stay decision is considered, the two alternatives each household encounter are "evacuate" and "stay". The probability of evacuation, represented by alternative "1", is expressed by Eq.(3.1).

$$\mathrm{Prob}[y = 1|\mathbf{x}, \boldsymbol{\beta}] = \Lambda(\boldsymbol{\beta}'\mathbf{x}) \tag{3.1}$$

where $\Lambda()$ represents the logistic distribution, $\mathbf{x}$ is the covariate vector for explanatory variables like household characteristics and $\boldsymbol{\beta}$ is the coefficient vector associated with the covariate vector $\mathbf{x}$. The major distinction of the mixed logit model used here from the regular binary logit model is the inclusion of covariates for the mean of the random parameters. To allow the mean of the certain random coefficients in vector $\boldsymbol{\beta}$ to vary across households, the coefficient vector $\boldsymbol{\beta}$ can be parameterized as Eq. (3.2) according to Greene (2012).

$$\boldsymbol{\beta} = (\boldsymbol{\beta} + \Delta\boldsymbol{z}) + \boldsymbol{\Gamma}\boldsymbol{u} \tag{3.2}$$

where $\boldsymbol{z}$ is a vector that stores covariates related to the mean of the random parameter vector $\boldsymbol{\beta}$ and Δ is the fixed coefficients for these covariates, $\boldsymbol{\Gamma}$ is a non-negative definite diagonal matrix and some of its diagonal elements could be zero for deterministic parameters and $\boldsymbol{u}_i$ is a normal random vector with zero mean and unit variance (Greene, 2012). The mixed logit model is usually estimated by simulated maximum likelihood as suggested in Train (2002).

3.2 THE ESTIMATION RESULTS OF THE EVACUATE-STAY MODEL

The model is estimated using the Hurricane Ivan survey data. Telephone interviews were conducted with 3,200 households from four states, namely Florida, Alabama, Mississippi, and Louisiana after Hurricane Ivan made landfall near Gulf Shores in 2004. Information collected included household socio-demographics, past hurricane experience, and evacuation decisions. Florida International University's Institute for Public Opinion Research conducted these surveys in English and Spanish with the assistance of a Computer Assisted Telephone Interviewing system.

3.2.1 Descriptive Analysis

Table 3.1 shows the sample characteristics and the association of covariates with the evacuation decision. The households' distances to the coast are calculated using their home coordinates and then normalized by the maximum distance to derive the relative distance to the coast, denoted by "[reldist]".

Table 3.1 Sample Characteristics of Explanatory Variables and Their Association with the Evacuation Decision for Hurricane Ivan

Variables	Sample Mean[a]	Crude Odds[b]	Adjusted Odds[b]	Likelihood Effect (Adjusted Odds)
[evac] = 1	44.31%	/	/	/
Socio-Demographics				
[bizown] = 1	17.84%	0.831 (0.085)*	0.785 (0.105)*	⇓
[mobile] = 1	6.12%	2.566 (0.435)***	3.476 (0.755)***	⇑
[childu17]	0.673	1.194 (0.044)***	1.148 (0.053)**	⇑
[inco80k] = 1	28.70%	1.211 (0.117)**	1.284 (0.147)**	⇑
[lthighsc] = 1	5.28%	0.656 (0.120)**	0.599 (0.143)**	⇓
[pgrad] = 1	16.50%	1.574 (0.166)***	1.576 (0.218)**	⇑
[reldist]	0.369	0.683 (0.242)***	0.663 (0.161)*	⇓
[pet] = 1	63.90%	0.782 (0.063)**	0.764 (0.081)**	⇓
[stateFL] = 1	40.10%	0.366 (0.031)***	0.353 (0.044)***	⇓
Evacuation-Related				
[haswkduty] = 1	32.80%	0.917 (0.076)	0.825 (0.088)	
[winprotect] = 1	54.23%	0.784 (0.061)**	0.682 (0.069)*	⇓
[noevacnt] = 1	54.12%	0.209 (0.017)***	0.141 (0.019)***	⇓
[nonmandnt] = 1	26.27%	1.793 (0.158)***	0.400 (0.060)***	⇓
[mandnt] = 1	19.59%	5.772 (0.650)***	*r*	⇑

a. Sample mean for the binary variable expresses the sample distribution. For example, there are 17.84% of the households who own businesses.
b. Crude odds are derived from uni-variable logistic regression and adjusted odds from multi-variable logit model.
r: Reference category, "⇑" indicates increased likelihood and "⇓" indicates decreased likelihood.
Standard error of odds in parentheses. * ~ $p < 0.01$, ** ~ $p < 0.05$, *** ~ $p < 0.001$

A few socio-demographic factors exhibit statistically significant impact upon evacuation decision. Households living in mobile homes, though there is only a limited number in the sample, are much more likely to evacuate than those who do not. Similarly, households that own businesses are less likely to evacuate possibly due to their concerns of protecting their businesses from post-storm looting. Households that have pets are less likely to evacuate. Households with higher income and education attainment are more likely to evacuate. The number of children under 17 also shows a positive impact upon the evacuation implying that one more child under 17 years old increases the odds of evacuating.

In terms of window protection, the adjusted odds are 0.682 and statistically significant at the 0.1 level, which suggests that households are less likely to evacuate after they used window protection. The work duty ("[haswkduty]") does not exhibit a statistically significant association with the evacuation decision in the single-variable logit model and regular multi-variable logit model. Households that had a member who had to work during the evacuation may have evacuated locally, evacuated without that member, or that person may have disregarded that obligation. This covariate is examined again in the next section. The evacuation notice had different impacts upon the households' evacuation decisions. The households that did not receive any evacuation notice ([noevacnt] = 1) are much less likely to evacuate than those who received mandatory evacuation notice and the crude odds and adjusted odds are highly significant. Households that received a non-mandatory evacuation notice are less likely to evacuate than those who receive mandatory notices, which is evidenced by a adjusted odds of 0.4. The effect of the warning messages will be further explored by using the subsequent random-parameter logit model.

3.2.2 The Random-Parameter Logit Model for Evacuate-Stay Decision

The selection of the variables is guided by the existing literature reviewed in Section 2.1. Normally distributed random coefficients are associated with three variables: "[haswkdut]", "[noevacnt]," and "[nonmandn]". Here, the normal distribution is used because the covariates' effects vary around the mean for the majority of the households and relatively large effects only show for a few households. Since the random parameters capture the heterogeneity among the household population, random parameters are first associated with all covariates and then the random coefficients that show statistical insignificance are set to be fixed parameters. The statistical significance of the mean and variance of the random parameter associated with "[haswkdut]" leads to its inclusion in the model. The random coefficients of the latter two variables capture households' different perceived risk of the approaching hurricane, which contributes to their evacuate-stay decisions. The model parameters are estimated using NLOGIT 5 and the estimation results are shown in Table 3.3.

The mean structure of the three random parameters (homogeneous mean or heterogeneous mean) is determined by including explanatory variables as shown in Eq. (3.2). . The statistically insignificant explanatory variables, represented by vector **z** in Eq. (3.2), in the mean of the random parameters are removed. Following this logic, a statistically significant heterogeneous mean is found for the random coefficient of “[noevacnt],” which associates the perceived risk with the relative distance to coast. Specifically, the normal distributions for the random coefficients of the three variables, namely “[haswkdut]”, “[noevacnt],” and “[nonmandn]” are shown in Table 3.2. Two variables, namely “[haswkdut]” and “[nonmandn]”, have homogenous means across households while the variable [noevacnt] has a heterogeneous mean across households that depend on two covariates, namely “[stateFL]” and “[reldist]” that are represented by vector **z** in Eq. (3.2).

Table 3.2 The Parameters of the Normally Distributed Random Coefficients

Variable	**Mean**	**Variance**
[haswkdut]	-0.197	1.231
[noevacnt]	-1.428+1.020×[stateFL]-0.976×[reldist]	0.628
[nonmandn]	-0.667	0.618

Table 3.3 The Estimation Results of the Evacuate/Stay Choice Model

Variable	**Description**	**Evacuate/Stay Model**
Nonrandom parameters		*Coefficient (Standard Error)*
[winprote][a]	The HH has window protection	-0.309*** (0.077)
[bizown][a]	A HH owns business	-0.198* (0.104)
[childu17]	Number of Children under 17	0.105*** (0.034)
[mobile][a]	HH lives a mobile home	1.078*** (0.171)
[inco80k][a]	HH's income is over 80,000 USD	0.202** (0.088)
[lthighsc][a]	HH's education level is less than high school	-0.396** (0.183)
[pgrad][a]	HH's education level is post-graduate	0.355*** (0.106)
[pet][a]	HH owns pet(s)	-0.201** (0.081)
[reldist]	HH's relative distance to coast	-0.530** (0.231)
[statefl][a]	HH lives in Florida	-0.805*** (0.100)
[Constant]		1.470*** (0.164)
Means for Random Parameters		
[haswkdut][a]	HH's members had work duty before evacuation	-0.197** (0.083)
[noevacnt][a]	HH did not receive evacuation notice	-1.428*** (0.163)
[nonmandn][a]	HH received non-mandatory evacuation notice	-0.667*** (0.113)
Variances for Random Parameters		
[haswkdut]		1.231*** (0.112)
[noevacnt]		0.628*** (0.080)
[nonmandn]		0.618*** (0.102)
Heterogeneity in the mean of [noevacnt]		
[stateFL]		1.020*** (0.210)
[reldist]		-0.976** (0.425)
a. This variable is an indicator variable which takes value “1” if the statement is true. Number of Observations: 2679, Log likelihood = -1183.348, Outcome = 1 represents a household chose to evacuate. $\chi 2$= 29.56 and P-value for chi-square test = 0.003. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.		

The model is statistically significant as shown by the likelihood chi-square test whose null hypothesis that all coefficients are zero is rejected at the 0.001 significance level. The fixed coefficients for the socio-economic factors generally show effects similar to existing studies (e.g., Yin et al. (2012a)). Specifically, the negative sign of the variable “[winprote]” indicates that the households that have window protection are less likely to evacuate, which is evidenced by the odds ratio of 0.734 (=exp(-0.309)) confirming the findings in the descriptive analysis. Possibly, the households that used window protection intended to stay while those that did not want to stay dismissed the necessity to apply measures to protect the home. Similarly, households that own businesses are less likely to evacuate as evidenced by the negative coefficient of covariate “[bizown]” -0.198, possibly due to their concerns of protecting their businesses from post-storm looting. A similar effect is observed for households who own pets. Households that have pets are less likely to evacuate possibly due to their accommodation concerns given to the pets’.. In addition, households in mobile residences are more likely to evacuate with the odds ratio of 2.938 (=exp(1.078)); these residences are more vulnerable to hurricane damage. As expected, households with higher income and education attainment are more likely to evacuate since these households generally have better access to resources necessary for evacuation such as means of transportation. Specifically, the odds ratios for households with income over than $80,000 are approximately 1.3 times as likely to evacuate and those households with post-graduate degrees holders are almost 1.5 as likely to evacuate. The number of children under 17 also shows a positive impact upon the evacuation. The odds ratio is exp(0.105) = 1.11 implying that one more child under 17 years old increases the odds of evacuating.

The effect of an evacuation notice is clearly consistent with existing literature. Households that do not receive mandatory evacuation notices are less likely to evacuate. The household-level heterogeneity of the random coefficient for the variable “[noevacnt]” allows households who do not receive any evacuation notice to assume different distributions for the random parameter depending on their distance to coast as show in Table 3.2. Specifically, the sign of the relative distance to coast is -0.976 for the mean of the random parameter of variable “[noevacnt]”, suggesting that the likelihood of evacuation for households that did not receive any evacuation notice decreases as their distance to coast increase on average.

3.3 EXAMINATION OF THE GEOGRAPHICAL EXTENT OF SHADOW EVACUATION

For the purpose of evacuation planning, the emergency planning agency may need to examine different shadow evacuation scenarios in terms of the geographical extent. For instance, in no-notice evacuation, shadow evacuation may occur in the region that fall within a specific distance (e.g., 3 mile) of the designated evacuation zone as suggested in Murray-Tuite et al. (2012a). The evacuate-stay model developed in Section 3.2 can be used to construct different scenarios of shadow evacuation after a distance sensitivity factor (DSF) is introduced. As shown in Table 3.3, the distance to coast variable “[reldist]” takes a negative sign in both the fixed effect and the heterogeneous mean for the random coefficient of variable “[noevacnt]”. This suggests that the perceived risk is sensitive to their distance to the coast but the sensitivity decreases as the distance to the coast increases. Therefore, if a scenario where a large shadow evacuation region is desired, one can increase the likelihood of evacuation for households outside the evacuation zone by diminishing the households’ sensitivity to the distance to coast. In other words, if a household living far from the coast is not sensitive to their distance to coast, it is as likely to evacuate as one household living close to the coast if all covariates are identical for the two households.

Here, the distance sensitivity factor, or DSF, is introduced for the two coefficients of the variable “[reldist]”, one in the fixed effect and the other in the heterogeneous mean equation as shown in the second row of Table 3.2. The current estimates, -0.530 for the fixed effect and -0.976 in the heterogeneous mean equation are considered to be the baseline case, where the DSF = 100%. To expand the geographical extent of shadow evacuation, the two coefficients are revised to be the product of the baseline estimates and the DSF (-0.530×DSF and -0.976×DSF). Hence, if the DSF is 0%, suggesting complete insensitivity to the distance to coast, the two coefficients become zero, which completely eliminate the effects of distance. Figure 3.1 shows the probability of evacuation under different Distance Sensitivity Factor (DSF) for a potential shadow evacuation household that does not receive any evacuation notice ([noevacnt] = 1). Other covariates for the household characteristics are held at their respective sample means. Clearly, when DSF = 0%, the probability of evacuation does not change with distance to coast. As DSF increases, the probability of evacuation becomes increasingly sensitive to the distance to coast. However, the effect of DSF is non-linear due to the non-linearity of the logistic distribution.

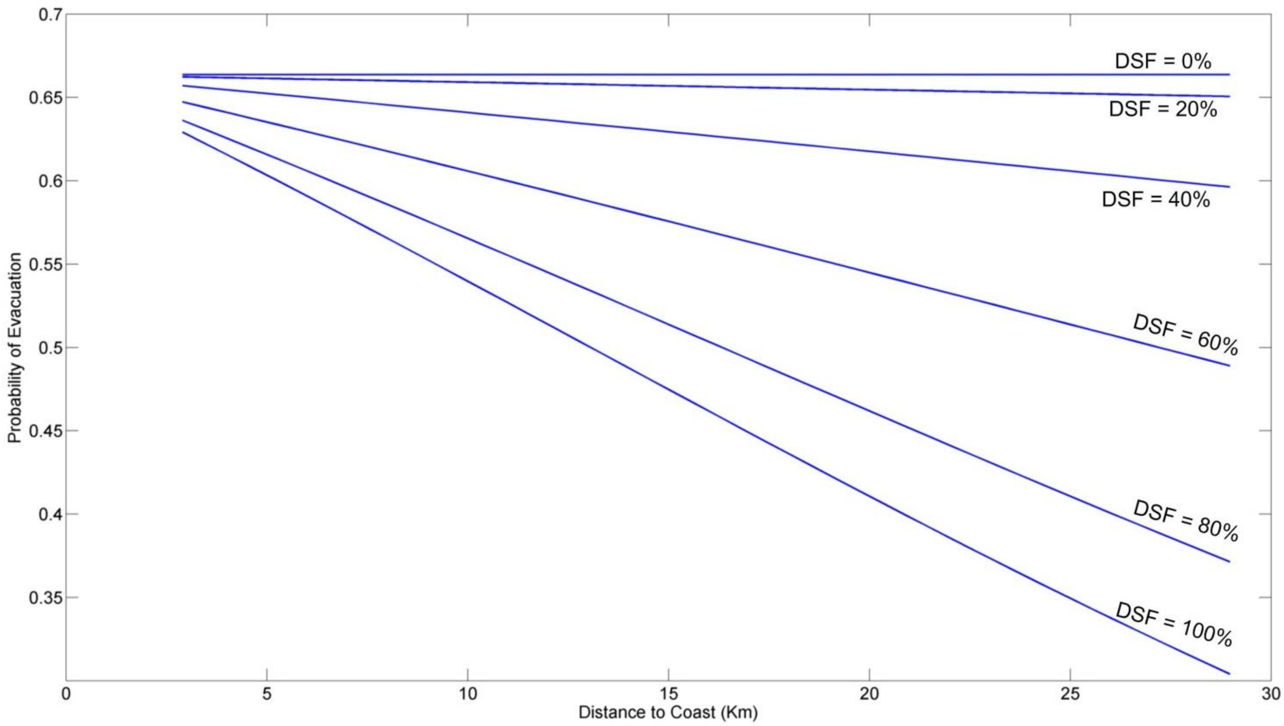

Figure 3.1 The Probability of Evacuation under Different Distance Sensitivity Factor (DSF) for a Potential Shadow Evacuation Household

To demonstrate the different geographical extent of shadow evacuation, the evacuate-stay model is applied to the Miami-Dade area under a hypothetical category-4 hurricane. A synthetic population is constructed using Census data along with the population synthesizer provided by the TRANSIMS package (Ley, 2009). Then the evacuate/stay choice model is applied to each synthetic household with its characteristics as covariates. To visualize the results, ArcGIS's kernel density tool is used to generate a smooth representation of the geographical extent of evacuation. The heat maps depicted in Figure 3.2, Figure 3.3 and Figure 3.4 represent the scenarios of different DSF values. Dark color indicates more evacuating households and light color including white color suggests fewer evacuees. A progression into the inland area is apparent in the figures. Specifically, the heat map in Figure 3.2 suggests that the major proportion of the shadow evacuation population lies within 3 km (1.86 miles) to 5 km (3.11 miles) of the mainland coastline when the DSF = 100%. When DSF decreases to 40%, the geographical extent of the shadow evacuation population extends to the 15-km (9.32 miles) line while the major proportion concentrates between 3 km (1.86 miles) to 10 km (6.21 miles). When DSF decreases to 0%, more shadow evacuation households show though its distinction from the case of DSF = 40% in Figure 3.3 is not enormous. This is because of the non-linearity of the effect of DSF as exhibited in Figure 3.1.

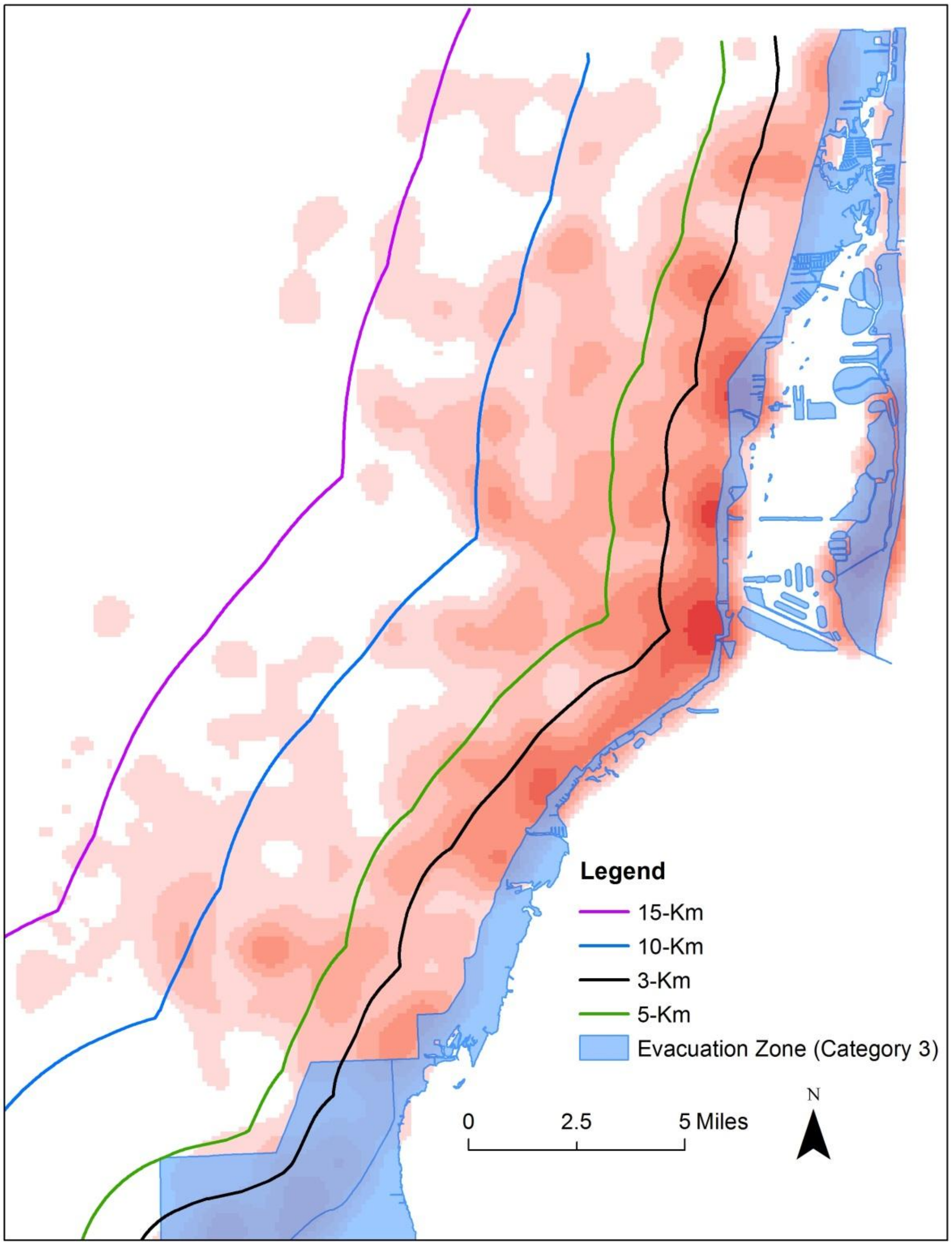

Figure 3.2 The Geographical Distribution of the Evacuation Population, DSF = 100% (Darker red indicates more evacuees)[1]

[1] The light red cells beyond the coastline outside the evacuation zone on the mainland and the island are generated by the kernel density algorithm of ArcGIS Spatial Analyst, which results in the inconsistent alignment between the evacuation zone and the

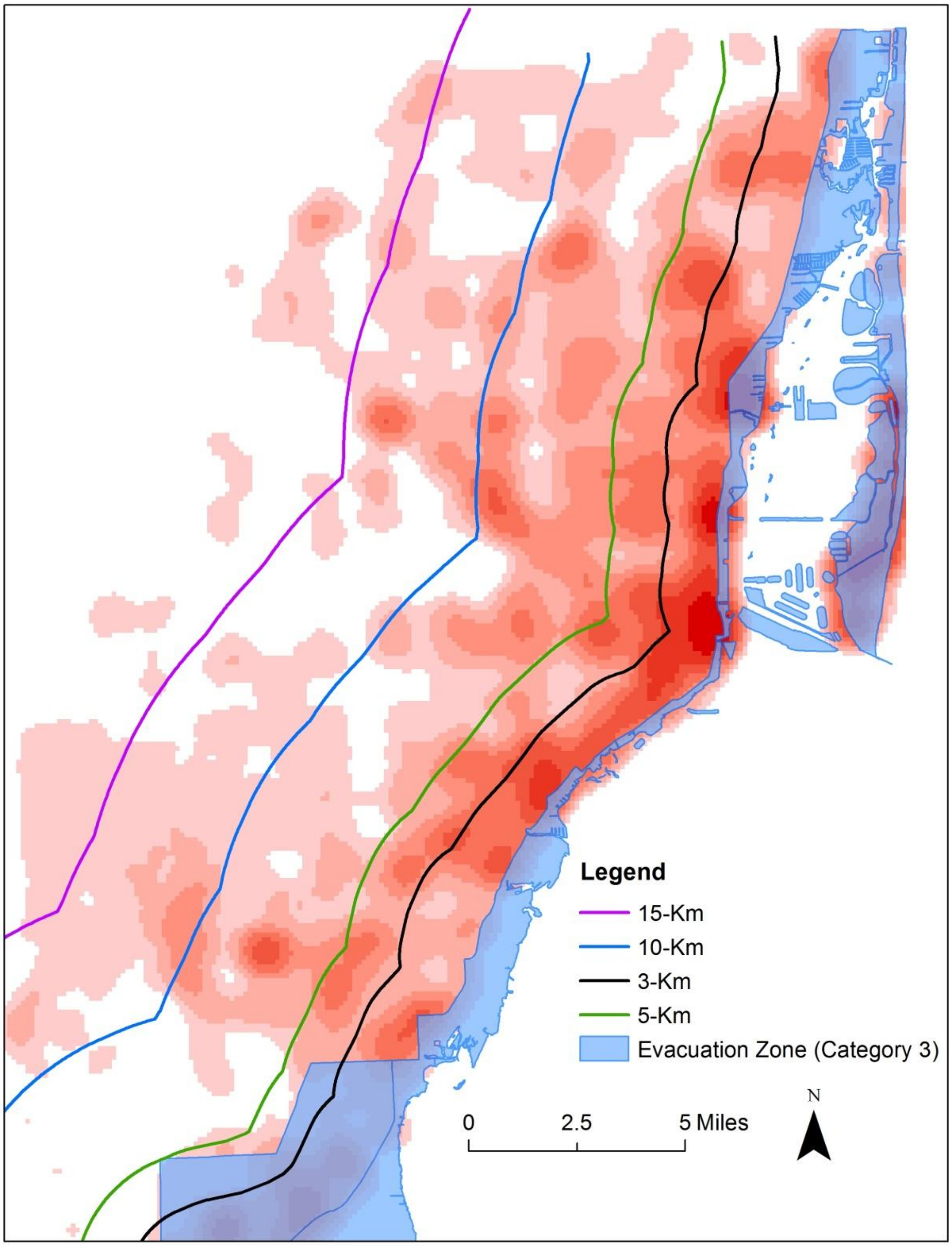

Figure 3.3 The Geographical Distribution of the Evacuation Population, DSF = 40% (Darker red indicates more evacuees)

heat map layer. There are no evacuees in those red cells beyond the coastline. The main purpose of this figure is to illustrate the extent of shadow evacuation that extends to inland areas.

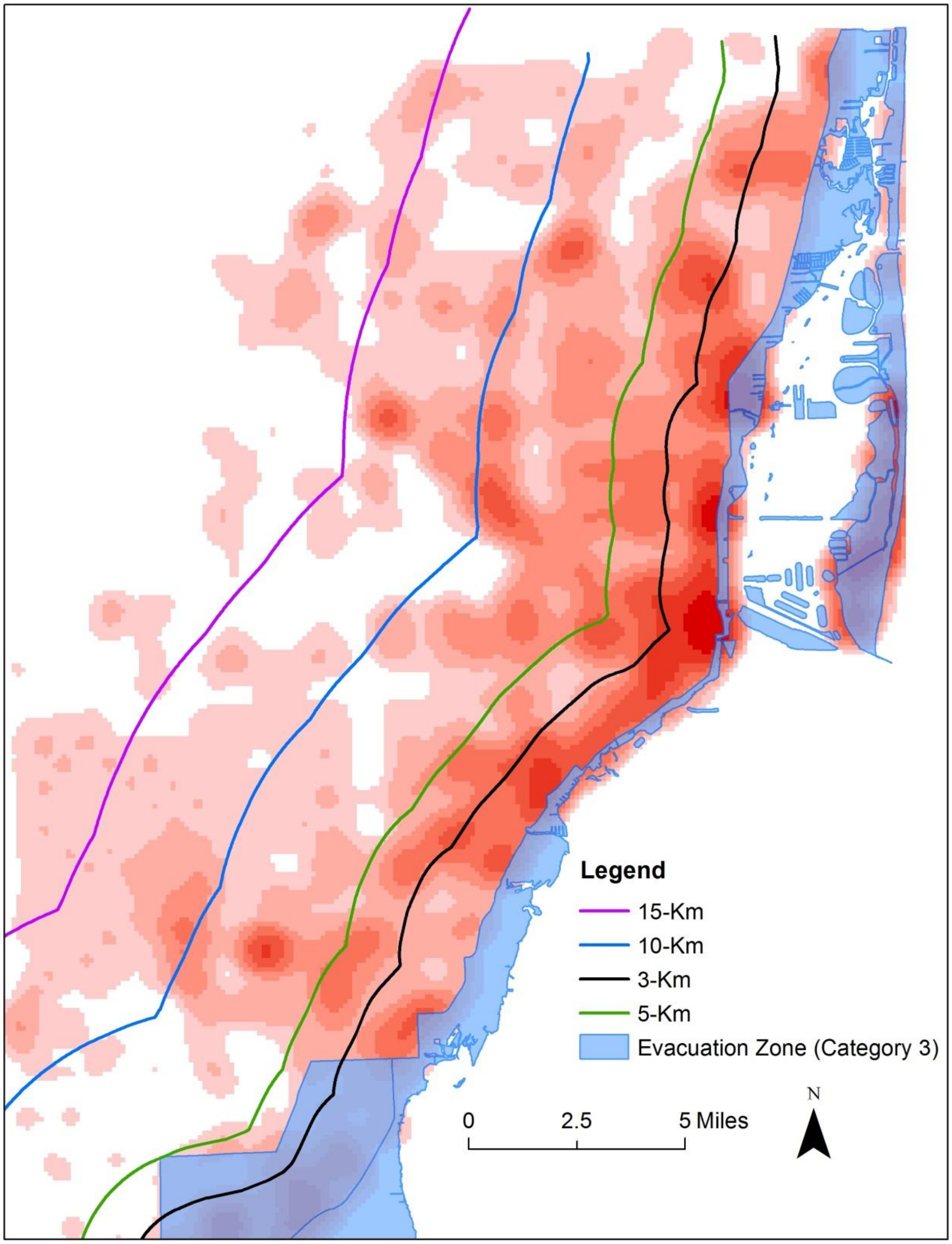

Figure 3.4 The Geographical Distribution of the Evacuation Population, DSF = 0% (Darker red indicates more evacuees)

3.4 SUMMARY

This chapter is among the first attempts to examine households' evacuate/stay choice by adopting a random-coefficient binary logit model with the capability of capturing the shadow evacuation. Random coefficients are associated with the variables representing the receipt of non-mandatory evacuation notices and the absence of evacuation notices. The statistical significance of the random coefficients explains the shadow evacuation phenomenon. In addition, the effects of multiple socio-demographic factors and evacuation-related covariates are investigated.

This study provides useful insights for a better understanding of household hurricane evacuation decision and provides practical emergency management implications. Several important factors are found to influence a household's decision to evacuate or stay at home. For forecasters and emergency managers, it confirms a series of factors people have to consider in their evacuation decision. Specifically, the households that have window protection are less likely to evacuate. Similarly, households that own businesses are less likely to evacuate possibly due to their concerns of protecting their businesses from post-storm looting. Households that have pets are less likely to evacuate. In addition, households in mobile residences are more likely to evacuate. Due to their relatively abundant financial means, households with higher income and education attainment are more likely to evacuate. The emergency management agencies probably need to allocate more resources to attend the needs of the households who are financially challenged. The number of children under 17 also shows a positive impact upon the evacuation.

In addition, the model provides econometric evidences supporting that households may respond in a heterogeneous manner if they receive a voluntary evacuation notice or they do not receive any evacuation notice. The study suggests that households that do not receive any evacuation notice are generally less likely to evacuate. Recognizing the fact that households' perceived risk is possibly related to their distance to the coast, it is found that the likelihood of evacuation for households that do not receive any evacuation notice decreases as their distance to coast increase on average. The distance sensitivity factor, or DSF, is introduced to construct the different scenarios of geographical extent of shadow evacuation. The study provides implications for both emergency management and evacuation modeling. The emergency management agencies should understand that the geographical extent of shadow evacuation may be extensive and thus should be prepared for the additional demand generated from the low-risk areas and relevant traffic management strategies and plans should be designed. The model offers the emergency management agencies the flexibility to investigate different levels of shadow evacuation when necessary. The household-level model can be easily implemented in an agent-based modeling and simulation framework and this model is later integrated with other evacuation choices into the demand model system described in Chapter 6.

CHAPTER 4 A STATISTICAL ANALYSIS OF THE NUMBER OF HOUSEHOLD VEHICLES USED FOR HURRICANE IVAN EVACUATION

This chapter presents a paper that has been accepted for presentation in the 93rd Annual Meeting of the Transportation Research Board, 2014. It was co-authored by Weihao Yin, Pamela Murray-Tuite, Satish Ukkusuri and Hugh Gladwin.

ABSTRACT

The objective of this paper is to identify the contributing factors to households' choice of the number of vehicles used for evacuation and develop predictive models of this choice that explicitly consider the constraint imposed by the number of vehicles owned by the household. This constraint is not accommodated by ordered response models. Data comes from a post-storm survey for Hurricane Ivan. The two models developed are variants of the regular Poisson regression model: the Poisson model with exposure and right-censored Poisson regression. The right-censored Poisson model is preferred due to its inherent capabilities, better fit to the data, and superior predictive power. The multivariable model and individual variable analyses are used to investigate seven hypotheses. Households traveling longer distances or evacuating later are more likely to use fewer vehicles. Households with prior hurricane experience, greater numbers of household members between 18 and 80, and pet owners are more likely to use a greater number of vehicles. Income and distance from the coast are insignificant in the multivariable models, although their individual effects have statistically significant linear relationship. However, the Poisson based models are non-linear. The method for using the right-censored Poisson model for producing the desired share of vehicle usage is also provided for the purpose of generating individual predictions for simulation.

KEYWORDS

Evacuation; hurricane; vehicle usage; number of vehicles; right-censored Poisson model

4.1 INTRODUCTION

Predicting hurricane evacuation traffic is a complex process that involves a series of models that attempt to replicate household decisions as well as the interactions of demand and infrastructure. Accurate demand representations are essential inputs to traffic simulation to estimate clearance times or other performance measures and to evaluate evacuation management strategies. Evacuation demand is governed by many factors, such as hurricane trajectory and household characteristics (Baker, 1991b; Carnegie and Deka, 2010; Gladwin et al., 2001; Urbina and Wolshon, 2003). A large body of work focuses on identifying which households would evacuate (see for example summaries in (Murray-Tuite and Wolshon, 2013a) and (Sorensen, 2000)), but the number of households evacuating does not directly translate into vehicle volumes. While some segments of the population rely on transit or emergency management agencies for evacuation transportation, private vehicles remain the preferred method of transportation. Some households take more than one vehicle, as observed in many post-storm surveys (Dow and Cutter, 2002b) (Lindell et al., 2005). Traffic simulation models can account for households taking multiple vehicles, but the rationale for the household decisions is not well researched (Dow and Cutter, 2002b). Additionally, a method for generating the individual prediction of household vehicle usage based on household characteristics is needed for traffic simulation applications. This paper is among the few to provide insights on the connections between household characteristics and the number of vehicles used for evacuation. The models presented here quantify the effects of household characteristics on vehicle usage in evacuations, which facilitates predictive analysis for future hurricane evacuation studies.

Despite its ordinal nature, vehicle usage (number of vehicles used) cannot be simply modeled using the discrete choice models for an ordered response. These models, such as the ordered logit model, assume that each decision-making entity, here a household, encounters an identical choice set. However, this assumption is violated in our context because the number of vehicles used cannot exceed the number of vehicles available to (owned or leased by) the household. Since not all households have the same numbers of vehicles, the households have different choice sets. This paper presents two variants of the Poisson regression model, namely the Poisson regression with exposure and right-censored Poisson regression, for the vehicle usage choice based on a post-storm survey for Hurricane Ivan. These two models account for the vehicle ownership constraint upon vehicle usage via different statistical specifications, which are estimated and compared to offer insights on the effects of contributing factors and prediction capabilities.

In addition to the investigation of various factors related to the vehicle usage choice, this paper briefly discusses how to generate individual predictions that well conform to a desired distribution of number of vehicles used. This approach improves Cova and Johnson's (2002) method by considering individual heterogeneity based on the estimated regression model.

This paper is divided into six additional sections. The next section reviews literature on vehicle usage during evacuations. The subsequent section provides an overview of the Hurricane Ivan data. The fourth presents descriptive statistical analyses and seven hypotheses to guide the multivariable statistical analysis. The fifth section outlines the modeling methodology along with a discussion of the estimation results. The last section provides conclusions and future directions.

4.2 Literature Review

Households' vehicle usage choice rarely has been strictly modeled for evacuations. Some studies did not present their methods for estimating the number of evacuating vehicles per household while others reported the average from survey results (2007c). Though existing research identifies the importance of having the household together as a condition for evacuating, it does not necessarily mean that households will evacuate in a single vehicle (Dow and Cutter, 2002b). Table 4.1 summarizes the literature's major findings related to vehicle usage in evacuation. While the averages or ranges shown in the table can be useful for quick assumptions, greater precision and identifying influencing factors can lead to better predictions of traffic conditions. For example, at the widest range, given 1,000,000 households, the number of vehicles ranges from 1,100,000 to 2,150,000, with clear implications for traffic conditions and clearance times.

Table 4.1 Summary of Findings of Vehicle Usage for Permanent Residents in Emergency Evacuation Literature

Study	The Number of Vehicles Used (Mean or Range)	Method	Emergency
Radwan et al. (1985) Sorensen (2000)	All vehicles in the Households	Subjective Assumption	Natural Disaster
Cova and Johnson (2002)	Random Simulation by Poisson Distribution	Simulation	Wild Fire
Ruch and Schumann (1997); (Ruch and Schumann, 1998)	1.35, 1.41	Stated-Preference Survey	Corpus Christi Area and Houston/Galveston Area Hurricane
Lindell et al. (2002) Lindell (2008)	1.62	Stated-Preference Survey	Texas Gulf Coast Area Hurricane
PBSJ Inc. (1999)	1.21 ~ 1.54	Revealed-Preference Survey	Hurricane Georges
Dash and Morrow (2000)	1.70	Revealed-Preference Survey	Hurricane Georges (Florida Keys)
Prater et al. (2000)	1.34	Revealed-Preference Survey	Hurricane Bret
Dow and Cutter (2002b)	1.26	Revealed-Preference Survey	Hurricane Floyd
Lindell et al. (2011); Lindell et al. (2005)	1.10 ~ 2.15	Revealed-Preference Survey	Hurricane Lili
Siebeneck and Cova (2008)	1.15 ~ 1.85	Revealed-Preference Survey	Hurricane Rita
Wu et al. (2012)	1.42 (0.12 Trailers)	Revealed-Preference Survey	Hurricane Katrina & Rita

The existing literature generally analyzed the sample characteristics based on stated-preference or revealed-preference surveys administered after the storm. Exceptions include Radwan et al. (1985) and Sorensen (2000) who assumed that all household vehicles would be used, which might overestimate the number of vehicles since many households own more than two. Another notable exception is the study by Cova and Johnson (2002), who modeled the number of evacuating vehicles using a Poisson distribution with the mean for the number of evacuating vehicles per residential household equal to the number of vehicles owned, which results in a distribution with a mode of 2 and a range from 0 to 6. However, they did not consider individual heterogeneity in the mean.

Several studies provided the sample average (always more than one) and range for the vehicle usage based on revealed-preference surveys. In addition to the average, Dow and Cutter (2002b) explored the relationship between certain household characteristics and vehicle usage based on Pearson correlation and observed a statistically significant correlation between vehicle usage and household size and income. They found that larger households are more likely to take more than one car. The same relationship was found between household income and vehicle usage with a relatively lower statistical significance. Similar observations were made by Lindell et al. (2011) using the Pearson correlation measure: younger evacuees who were married and had larger households with children and higher incomes tended to take more vehicles and were more likely to take a trailer, based on a survey for Hurricane Lili. They also found that evacuees living closer to the coast take more vehicles. Later, they (Wu et al., 2012) conducted similar research for Hurricanes Katrina and Rita and found that evacuees took 1.42 vehicles on average, consistent with Lindell and Prater (2007a).

Some authors also considered vehicle usage choice by transient dwellers such as tourists. Lindell (2008) assumed that transient dwellers would be less likely than permanent residents to have multiple vehicles available, so they are assumed to use only one vehicle for evacuation. Hobeika et al. (1994) noted that some tourists arrived and departed the risk area in tour buses.

While the previous studies provided valuable insights into the vehicle usage choice, they mainly employed uni-variable qualitative technique without considering their confounding effects simultaneously. This study contributes to the literature by using a multi-variable statistical technique, which uncovers the relationship between vehicle usage and various factors in a quantitative fashion.

4.3 OVERVIEW OF THE DATA

This study’s data are from a survey of households in Florida, Alabama, Mississippi, and Louisiana after Hurricane Ivan made landfall near Gulf Shores, Alabama, in September 2004. Telephone interviews were conducted with 3,200 households from these four states. Information collected included household socio-demographics, past hurricane experience, and evacuation preparations and decisions.

Since vehicle usage for evacuation is the dependent variable of interest, only the 1,443 households that evacuated were selected from the original sample. After the records with missing values for key covariates, such as travel distance to the evacuation destination, vehicle ownership, and the dependent variables were discarded, 853 records remained for subsequent descriptive analysis and model estimation.

4.3.1 Variable Selection

The existing literature provides some guidance for variable selection such as household income (2002b) (2011), household size (2011), and households' distance to the coast (2011), which will be considered here in addition to other variables. The independent variables fall into two general categories: household characteristics and evacuation-related characteristics. The independent variables are shown in Table 4.2 and their effects will be discussed in the following analysis.

4.3.2 Research Hypotheses

To augment previous studies, we examine the following hypotheses to guide the subsequent multi-variable regression analysis.

H1: Households that travel longer distance are more likely to use fewer vehicles. This hypothesis is based on the household's preference to stay together during the evacuation as suggested by Sorensen (2000); more vehicles may increase the risk of being scattered in traffic. Furthermore, longer distances may require multiple drivers.

H2: Households who evacuate late are statistically more likely to use fewer vehicles. Despite Lindell et al.'s [19] findings that evacuation decision time was not significantly correlated with vehicle usage, they were considering the influence of the use of relying on others for transportation rather than the number of vehicles. Previous studies (e.g., (Hasan et al., 2013b; Murray-Tuite and Wolshon, 2013a; Murray-Tuite et al., 2012)) have shown that more households depart closer to the day of hurricane landfall, which often results in severe congestion. Households may prefer to travel together in highly congested situations.

H3: Households' previous hurricane experience contributes to their vehicle usage choices; those with prior experience are statistically more likely to use a greater number of vehicles. Experienced households may bring more personal items or evacuation supplies, which requires more space. They may also have experienced vehicle damage if they left vehicles at home in previous hurricanes, making them more likely to try to protect these personal assets.

H4: The number of household members between 18 and 80 is positively related to the number of vehicles taken on the evacuation. Previous studies suggested that larger households are more likely to take more than one car (Dow and Cutter, 2002b; Lindell et al., 2011). This study uses a variable related to driving-aged adults, considering that they would be the most likely to drive household vehicles in stressful environments, such as evacuations.

H5: Household income is positively related to the number of household evacuation vehicles chosen. Previous studies found such a correlation between household income and vehicle usage (Lindell et al., 2011).

H6: Pet-owning households are statistically more likely to evacuate with more vehicles than households without pets. Pets require their own space and supplies and are anticipated to increase the number of vehicles a household chooses to use.

H7: Households living farther from the coast are less likely to take more vehicles that those living close to the coast. A previous study found a negative linear correlation between the number of vehicles and the distance to the coast (Lindell et al., 2011).

Table 4.2 List of Variables and Descriptive Statistics

Variable	Description	Mean	Std. Dev.
[numvehu]	The number of vehicles used for evacuation	1.3810	0.6653
Evacuation-related Characteristics			
[logdist]	The log of the travel distance to the evacuation destination	4.5166	1.5540
[dur]	The stay duration in hours until evacuation[a]	51.1208	18.8522
[mandnt]	Whether the household received a mandatory evacuation notice	0.3283	0.4699
[nonmandnt]	Whether the household received a non-mandatory evacuation notice	0.3177	0.4659
[noevacnt]	Whether the household received no evacuation notice	0.3540	0.4785
[friend]	Whether the household went to a friend/relative's house for evacuation	0.6225	0.4850
[hotel]	Whether the household went to a hotel for evacuation	0.2227	0.4163
[shelter]	Whether the household went to a public shelter for evacuation	0.0234	0.1514
Socio-economic Characteristics			
[numveh]	The number of vehicles owned by the household	2.1290	0.7915
[bizown]	Whether the household owned any businesses	0.1618	0.3685
[hurrexp]	Whether the household had any hurricane experience before Ivan	0.7890	0.4083
[mobile]	Whether the household lived in a mobile home	0.0868	0.2816
[hhsize]	The household size	3.0645	1.5780
[childu17]	The number of children under 17 years old	0.7292	1.1029
[oldo80]	The number of people over 80 years old	0.0891	0.3343
[num18to80]	The number of people between 18 and 80 years old	2.2462	1.2335
[rent]	Whether the household lived in a rented property	0.0856	0.2799
[white]	Whether the householder is white	0.8734	0.3327
[income][b]	The household's income	3.6190	1.0959
[edu][c]	The household's highest educational attainment	3.4385	1.1248
[pet]	Whether the household had any pets	0.6307	0.4829
[distcoast][d]	The household's distance to coast	150.9456	97.9736
[stateAL]	Whether the household lived in Alabama	0.1430	0.3503
[stateFL]	Whether the household lived in Florida	0.2720	0.4452
[stateLA]	Whether the household lived in Louisiana	0.3400	0.4740
[stateMS]	Whether the household lived in Mississippi	0.2450	0.4304

a. The earliest hour specified in the survey 12:00 AM, Monday September 13, 2004 is used as the reference time to count the duration of stay until evacuation. It is the amount of time in hours between the reference time and household's departure time for evacuation.
b. The [income] variable has 5 levels, coded as "1" to "5" which indicates "<15,000", "15,000 to 24,999", "25,000 to 39,999", "40,000 to 79,999" and ">= 80,000". Separate indicator variables are used.
c. The [edu] variable has 5 levels, coded as "1" to "5", which indicates "less than high school", "high school graduate", "less than college", "college graduate", and "post graduate". Separate indicator variables are used.
d. The distance to coast is calculated using the coordinates of the household. The unit is kilometer (1 km = 0.61 mile).

4.4 DESCRIPTIVE STATISTICAL ANALYSIS

The descriptive statistical analysis starts with an examination of the sample characteristics of the explanatory variables. Then, the association between vehicle usage and these variables are investigated using statistical tests.

4.4.1 Sample Characteristics

Columns 3 and 4 of Table 4.2 provide the summary statistics of the variables. Among the households in the sample, the average number of vehicles used is 1.38, which is similar to previous literature.

The evacuation warning distribution was almost evenly split. A slightly higher percentage of households (32.83%) received a mandatory evacuation notice while 31.77 percent received a voluntary notice. The majority of the households (62.25%) sought accommodations in friends' or relatives' homes while 22.27 percent went to hotels and 2.34 percent chose public shelters.

Most of the households owned their houses; only approximately 8% lived in rented properties. Mobile home residents, though limited (8.68%), were captured as well. In terms of income level, on average, households earned over 40,000 USD. In terms of respondents' geographical distribution, Louisiana had the most respondents followed by Florida.

Association between Vehicle Usage Choice and the Explanatory Variables

The cross tabulation of vehicle ownership and vehicle usage choice for Hurricane Ivan is shown in Table 4.3. Similar to previous studies' observations, 66.71% of the households used only one vehicle, 25.91% used two vehicles, and 6.10% used more than 3 vehicles. Only 42.32% of the households used all the vehicles they owned, suggesting that the assumption of using all the household's vehicles is not reflective of reality.

Table 4.3 Cross Tabulation between Vehicle Usage Choice and Vehicle Ownership

	Number of Vehicles Owned by Households						
Number of Vehicles Used	1	2	3	4	5	7	Total
0	3	7	1	0	0	0	11
	35.00%	82.00%	12.00%	0.00%	0.00%	0.00%	1.29%
1	144	329	80	11	4	1	569
	16.88%	38.57%	9.38%	1.29%	0.47%	0.12%	66.71%
2	0	169	38	12	2	0	221
	0.00%	19.81%	4.45%	1.41%	0.23%	0.00%	25.91%
3	0	0	39	4	1	0	44
	0.00%	0.00%	4.57%	0.47%	0.12%	0.00%	5.16%
4	0	0	0	5	0	0	5
	0.00%	0.00%	0.00%	0.59%	0.00%	0.00%	0.59%
5	0	0	0	0	3	0	3
	0.00%	0.00%	0.00%	0.00%	0.35%	0.00%	0.35%
Total	147	505	158	32	10	1	853
	17.23%	59.20%	18.52%	3.75%	1.17%	0.12%	100.00%

Table 4.4 provides the correlation measures and results of independence tests between the vehicle usage choice and explanatory variables. Due to the ordinal-scale nature and non-normality of the dependent variable (vehicle usage), Spearman correlation is used instead of the Pearson correlation and the Kruskal Wallis test is used in place of the chi-square test to investigate the independence as suggested by Corder and Foreman (2009). The Spearman rank-order correlation measures the relationship between one ordinal-scale dependent variable (vehicle usage) and one ordinal-scale independent variable (e.g., household size) or ratio-scale variable like travel distance (Corder and Foreman, 2009). The Kruskal Wallis test is the non-parametric version of one-way analysis of variance (ANOVA) which permits two or more groups for independent categorical variables such as income level (Corder and Foreman, 2009; UCLA: Statistical Consulting Group, 2013).

4.4.1.1 Evacuation-Related Characteristics

The negative Spearman correlation -0.0987, statistically significant at the 0.05 significance level, between the logarithm of the travel distance to the evacuation destination and the number of vehicles used indicates households travelled with fewer vehicles if they went farther, possibly for reasons argued for Hypothesis 1. The correlations between types of evacuation warning received and the number of vehicles used also show various magnitudes of statistical significance. Specifically, the difference in the number of vehicles used between those receiving mandatory notices and those not receiving the mandatory notice is statistically significant at the 0.05 level, which points to the effect of risk level. The types of accommodations also affect the number of vehicles used. The difference between the households going to friends' or relatives' homes and those going other elsewhere is statistically significant at the 0.05 level. Households seeking shelter at friends' or relatives' homes brought an average of 1.34 vehicles, which is less than the average 1.45 vehicles used by households going to hotels. The households going to shelters had the lowest vehicle average, 1.30. Parking space considerations might contribute to this difference. Table 4.4 also shows a positive correlation between the number of vehicles used and the stay duration until evacuation though the effect lacks statistical significance in the uni-variable Spearman correlation analysis. However, later multivariable analysis shows statistical significance.

4.4.1.2 Household Characteristics

Households with hurricane experience exhibit statistically significant different behavior in terms the number of vehicles chosen for evacuation from first-time evacuees. The households with prior experience used 1.41 vehicles on average, 0.15 vehicles more than those who evacuated for the first time due to Hurricane Ivan. Perhaps the experienced evacuees tend to bring more items, which require more space. Confirming the findings of Dow and Cutter (2002b), the greater the household size, the more likely the household was to take more than one vehicle, as evidenced by the highly statistically significant correlation 0.14. Closer examination of the sample reveals that 37.64% of the households with three or four people took more than two vehicles. The number of household members aged between 18 and 80 is also positively related to the number of vehicles used, as expected. The number of senior citizens over 80 years old exhibits a negative correlation with the number of vehicles used with a relatively low statistical significance of 0.1. The number of children under 17 years old is insignificantly correlated with the dependent variable. The pet-owning households show a highly significant difference from those who did not own pets; pet owners use 0.22 vehicles more on average than those who did not own pets. The difference in vehicle usage between households with different income levels is statistically insignificant for both the continuous ([incomep]) and discrete versions of the income variable. This does not necessarily contradict Dow and Cutter (2002b) since a different sample and different statistical tests are used. Dow and Cutter (2002b) used the Pearson correlation coefficient, but this paper takes the ordinal-scale nature of vehicle usage into consideration and thus uses the Kruskal Wallis test. The identical observation can be made about the households with different educational attainment. But the test for the indicator variables generated for education attainment shows that the difference between households with post-graduate degree holders and those who do not is statistically significant. Households with post-graduate degree holders used 0.12 fewer vehicles on average than those without. The households living farther from the coast are more likely to take fewer vehicles, consistent with Lindell et al.'s finding (Lindell et al., 2011). The differences due to geographical locations are statistically significant for households in LA and MS at the significance level of 0.1; households in these two states used approximately 0.1 more vehicles (1.43 vehicles) than residents in the other two states on average (1.34 vehicles for FL and AL).

Though the univariate statistical testing shed some light on the relationships between the explanatory variables and the vehicle usage choice, they fail to offer quantitative assessment, which will be achieved via the subsequent regression modeling.

Table 4.4 Correlation Measures and Results of the Independence Tests for the Explanatory Variables

Variable	Correlation Measure	Correlation Test Significance	Correlation Test Method
[logdist]	-0.0987	0.0039**	Spearman Correlation
[dur]	0.0073	0.8324	Spearman Correlation
[mandnt]	/	0.0048**	Kruskal Wallis
[nonmandnt]	/	0.0911*	Kruskal Wallis
[noevacnt]	/	0.0893*	Kruskal Wallis
[bizown]	/	0.1875	Kruskal Wallis
[hurrexp]	/	0.0115**	Kruskal Wallis
[mobile]	/	0.0896*	Kruskal Wallis
[hhsizei]	0.1385	0.0000***	Spearman Correlation
[childu17i]	0.0232	0.4979	Spearman Correlation
[oldo80i]	-0.0616	0.0722*	Spearman Correlation
[num18to80]	0.2368	0.0000***	Spearman Correlation
[rent]	/	0.4956	Kruskal Wallis
[white]	/	0.6031	Kruskal Wallis
[income]	/	0.4387	Kruskal Wallis
[incu15k][a]		0.2505	Kruskal Wallis
[inc15to25k][a]		0.2088	Kruskal Wallis
[inc25to40k][a]		0.4945	Kruskal Wallis
[inc40to80k][a]		0.7491	Kruskal Wallis
[inco80k][a]		0.3410	Kruskal Wallis
[incomep]	0.0412	0.2295	Spearman Correlation
[edu]	/	0.1104	Kruskal Wallis
[lthighsch][b]		0.4908	Kruskal Wallis
[highsch][b]		0.0668	Kruskal Wallis
[ltcol][b]		0.1291	Kruskal Wallis
[colgrad][b]		0.9477	Kruskal Wallis
[pgrad][b]		0.0239**	Kruskal Wallis
[pet]	/	0.0001***	Kruskal Wallis
[friend]	/	0.0431**	Kruskal Wallis
[hotel]	/	0.2204	Kruskal Wallis
[shelter]	/	0.2485	Kruskal Wallis
[distcoast]	-0.0717	0.0362**	Spearman Correlation
[stateAL]	/	0.2643	Kruskal Wallis
[stateFL]	/	0.5454	Kruskal Wallis
[stateLA]	/	0.0744*	Kruskal Wallis
[stateMS]	/	0.0926*	Kruskal Wallis

* ~ p < 0.1, ** ~ p < 0.05, *** ~ p < 0.01
a. The indicator variables for the categories of variable [income] (less than $15,000; $15,000-$25,000; $25,000-$40,000; $40,000-$80,000; more than $80,000)
b. [incomep] is an artificially created continuous version of the categorical variable income. Its value is the median of the respective categories.
c. The indicator variables for the categories of variable [edu] (less than high school; high school graduate; some college; college graduate; post-college graduate)

4.5 REGRESSION ANALYSIS

The unique characteristic of the dependent variable - the number of vehicles used being constrained by the number of vehicles owned - is handled via two different approaches: Poisson regression with exposure

(PR-E) and right-censored Poisson regression (PR-C). The PR-E model explicitly includes the vehicle ownership as a regressor with a unity coefficient. Households that own more vehicles will be given higher probabilities of using more vehicles by the PR-E model. A household could be predicted to use more vehicles than they own since the PR-E specification may associate non-zero probabilities for numbers greater than the number of vehicles owned. The PR-C model will always give zero probabilities to numbers greater than the number of vehicles owned, by construction.

4.5.1 Modeling Methodology

Let y_i denote the number of vehicles used for household i. Then the probability of the random variable Y that denotes the number of vehicles used is given by Eq.(4.1) for a regular Poisson model.

$$\Pr(Y = y_i|\mathbf{x}_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, y_i = 0,1,2, \ldots \tag{4.1}$$

where $\mathbf{x}_i$ is the covariate vector for household i and λ_i is the expected number of vehicles used (Greene, 2012). The parameter λ_i is related to the covariates by a log-linear formulation as shown in Eq.(4.2),

$$\ln\lambda_i = \mathbf{x}_i'\boldsymbol{\beta} \tag{4.2}$$

where $\boldsymbol{\beta}$ is the parameter vector (Greene, 2012). The partial effects of the covariates with respect to the expected number of vehicles used is therefore given by Eq.(4.3).

$$\frac{\partial E[y_i|\mathbf{x}_i]}{\partial \mathbf{x}_i} = \lambda_i\boldsymbol{\beta} \tag{4.3}$$

It is natural to expect that a household that owns more vehicles would be more likely to use more vehicles than a household that owns fewer vehicles. While the number of vehicles owned can be simply used as a covariate in a regular Poisson regression model, another way of introducing this type of individual heteroscedasticity is to use the so-called exposure time specification (Greene, 2012; Long and Freese, 2006). Suppose the number of vehicles owned by the household is v_i, then the expected number of vehicles used is revised as Eq.(4.4).

$$\lambda_i v_i = \exp\left(\mathbf{x}_i'\boldsymbol{\beta}\right) v_i = \exp\left(\mathbf{x}_i'\boldsymbol{\beta} + \ln v_i\right) \tag{4.4}$$

This shows that the effect of the different vehicle ownership is included as the log of the number of vehicles owned with a regression coefficient constrained to be unity. By construction, the household that owns more vehicles will have a larger expected number of vehicles used due to the inclusion of the logarithm term. This model is referred to as Poisson regression model with exposure times (PR-E).

The number of vehicles used by a household cannot exceed the number of vehicles they own. Both of the previous formulations do not explicitly consider this constraint, which the Poisson model with right-censoring can handle. The probabilities of the number of vehicles used are constructed using the axioms of probability as suggested by Greene (2012), which produces Eq.(4.5).

$$\begin{cases} \Pr(y_i = j|\mathbf{x}_i) = \dfrac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} = P_{i,j}, j = 0,1,\dots,v_i - 1 \\ \Pr(y_i = v_i|\mathbf{x}_i) = 1 - \displaystyle\sum_{j=0}^{v_i-1} P_{i,j} \end{cases} \tag{4.5}$$

Therefore, the expected number of vehicles used is given by Eq.(4.6) (Greene, 2012),

$$E[y_i|\mathbf{x}_i] = v_i - \sum_{j=0}^{v_i-1} (v_i - j)\, P_{i,j} \tag{4.6}$$

Eq.(4.6) indicates that the expected number of vehicles used does not exceed the number of vehicles owned v_i by construction.

In a regular Poisson regression model, the effect of the vehicle ownership can be negative since there is no constraint upon the coefficient of the regressor. The PR-E specification guarantees that households that own more vehicles will be given higher probabilities of using more vehicles than those with fewer vehicles. However, the drawback of non-zero probabilities for numbers of vehicles larger than the number of vehicles owned is still present. The PR-C model improves this by introducing a more sophisticated probability structure as show in Eq. (4.5).

4.5.2 Model Estimation Results

The two Poisson regression models (PR-E and PR-C) are estimated using maximum likelihood estimation in Stata. The estimation sample is a random sub-sample which contains 757 observations (90%) of the original sample and the remaining 96 observations serve to examine the models' prediction capabilities. The estimation results are shown in Table 4.5. Not all of the explanatory variables shown in Table 4.2 are included since the variables statistically insignificant at the 0.1 level are removed from models based on stepwise likelihood ratio tests. Both models are statistically significant as shown by the likelihood chi-square test whose null hypothesis that all coefficients are zero is rejected at the 0.001 significance level.

The partial effect for an indicator variable, such as [hurrexp], is computed using discrete change while that for a continuous variable, such as travel distance ([logdist]) and stay duration until evacuation ([dur]), is computed using the partial derivative method given in Eq.(4.3). The partial effect for each observation is computed and then averaged to derive the average partial effect (APE) shown in Table 4.5. These APEs aid the discussion of the hypotheses.

H1: Households that travel longer distance are more likely to use fewer vehicles.

The travel distance to the evacuation destination shows a negative effect upon the vehicle usage in both formulations. Specifically, a unit change of the logarithm of the travel distance, i.e., extending the travel distance by about 2.7 times, leads to about 0.05 fewer vehicles in both the exposure formulation and the right-censored Poisson model, which supports H1.

H2: Households who evacuate late are statistically more likely to use fewer vehicles.

The stay duration until evacuation shows a statistically significant effect upon the vehicle usage in the regression analysis as opposed to the univariate association analysis. Generally, longer stay duration leads to fewer vehicles used, consistent with H2. A one hour increase in stay duration corresponds to an approximately 0.003 decrease in vehicle usage for the exposure formulation and the right-censored Poisson formulation, holding every other covariate constant.

H3: Households' previous hurricane experience contributes to their vehicle usage choices; those with prior experience are more likely to use a greater number of vehicles.

Prior hurricane experience has a statistically significant positive effect upon vehicle usage at the 0.001 level for right-censored Poisson model, supporting H3, but not in the exposure formulation. Having previous hurricane experience increases the number of vehicles used by approximately 0.14 in the right-censored Poisson model.

H4: The number of household members between 18 and 80 is positively related to the number of vehicles taken on the evacuation.

The number of people between 18 and 80 shows a statistically significant positive effect upon the vehicle usage choice in the right-censored Poisson model but not in the exposure formulation at the 0.1 significance level. One more person between 18 and 80 leads to a 0.1267 vehicle increase in the right-censored Poisson formulation. The Pearson correlation calculation reveals that the household size has a positive linear correlation with the number of vehicles used, which is consistent with existing findings (Dow and Cutter, 2002b; Lindell et al., 2011).

H5: Household income is positively related to the number of household evacuation vehicles chosen.

This hypothesis is not supported. Different from previous studies (Dow and Cutter, 2002b; Lindell et al., 2011), the income variable in both models is insignificant at the 0.1 level. Related to vehicle ownership, the effect of income is partly captured via the explicit treatment of vehicle ownership constraint upon the vehicle usage choice in both formulations. A related variable, being a post-graduate degree holder, decreases the number of vehicles used by about 0.1 in both the right-censored Poisson model and exposure formulation. The potentially conflicting results may be due to the different statistical techniques. The multi-variable modeling considers the ordinal nature of the number of vehicles used and explicitly treats other confounding factors and the effect of vehicle ownership in a nonlinear fashion. The Pearson correlation factor, used by previous studies (Dow and Cutter, 2002b; Lindell et al., 2011), treats the number of vehicles as a continuous variable and investigates a linear relationship. The Pearson correlation calculation for our sample is consistent with existing findings (Dow and Cutter, 2002b; Lindell et al., 2011).

H6: Pet-owning households are statistically more likely to evacuate with more vehicles than households without pets.

The support for this hypothesis depends on the model. Being a pet owner increases the number of vehicles used by about 0.12 in the right-censored formulation, supporting H6, but is insignificant at the 0.1 level in the exposure formulation.

H7: Households living farther from the coast are less likely to take more vehicles that those living close to the coast.

This hypothesis is not supported in the multivariable models. However, a negative statistically significant Spearman correlation was obtained in the descriptive analysis, which suggests that households living farther from the coast take fewer vehicles, consistent with Lindell et al. (Lindell et al., 2011).

Other socio-demographic factors also exhibit statistically significant impacts upon vehicle usage choice. Living in a mobile home increases the number of vehicles used by 0.23 for right-censored Poisson and 0.27 for the exposure formulation. Statistically significant geographical distinctions show in both models. Being a FL resident decreases the number of vehicles used by about 0.14 in the exposure formulation and 0.10 in the right-censored model, possibly because Florida did not suffer the strongest hurricane impact among the four states.

Table 4.5 Estimation Results of the Poission Regression Models

	Poisson with Exposure		Right-Censored Poisson	
	Estimates	Avg. Partial Effect	Estimates	Avg. Partial Effect
[numveh]	e		Censoring Variable	
	(0.0000)			
[logdist]	-0.0372***	-0.0519	-0.0618***	-0.0531
	(0.0117)		(0.0182)	
[dur]	-0.00238**	-0.0030	-0.00367**	-0.0031
	(0.00089)		(0.00143)	
[num18to80]	/		0.148***	0.1267
	/		(0.0309)	
[hurrexp]	/		0.159***	0.1369
	/		(0.0554)	
[incomep]	/		/	
	/		/	
[pgrad]	-0.0930**	-0.109	-0.129**	-0.1110
	(0.0474)		(0.0559)	
[pet]	/		0.144***	0.1235
	/		(0.0477)	
[mobile]	0.184***	0.257	0.264***	0.2263
	(0.0463)		(0.0961)	
[stateFL]	-0.101***	-0.141	-0.119**	-0.1021
	(0.0373)		(0.0511)	
Constant	-0.102	/	0.515***	/
	(0.094)	/	(0.156)	/
Number of Observations	767		767	
Log-Likelihood	-942.739		-708.685	
AIC	2.478		1.871	

4.5.3 Comparison between Models

The models are compared from four aspects. First, the model fit is evaluated based on likelihood values and Akaike information criterion (AIC). The right-censored Poisson regression model enjoys larger likelihood value -708.685 and a lower AIC value 1.871, which suggests it is the superior model. The models' performance are also evaluated based on the predicted aggregate share as suggested by Train (2002). The predicted shares of the two models along with the observed share for the hold-out sample are depicted in Figure 4.1. Both models increase the accuracy of the predicted shares upon the constant-only model. The censored Poisson model offers the best share prediction at all levels of the dependent variable, except when the number of vehicles used is two. At this particular level, the Poisson model with exposure slightly underestimates the share while the censored Poisson model overestimates the share. At the disaggregate level, when the Poisson mean is used for predicting the number of vehicles used, the censored Poisson model also provides better prediction performance in terms of root mean square error (RMSE) and mean absolute error (MAE), two measures suggested by Bhat and Pulugurta (1998).

For certain evacuation traffic simulation applications, the simulation of households' vehicle usage choices is of major interest (for an example in regular planning, see Bhat et al. (2002)). However, due to the inherent characteristics of the Poisson distribution, the simulated shares of the zero vehicles will be usually overestimated, which is demonstrated in Figure 4.1. Even the censored Poisson model, which offers the best performance, overestimates the percentage of the zero vehicles. Using Eq.(4.5), the probability of using no vehicles is given by $e^{-\lambda}$. For $\lambda = 2$, the percentage is 13.53%, which is higher than the observed sample share (1.29%).

Considering this probability is decreasing with the expected number of vehicles used, when the expected number of vehicles is less than 2, which is true for all estimated models, the percentage is even higher. Hence, some adjustment, such as the one proposed in this paper, is needed to produce the desired share. Here, both zero-vehicle and two-vehicle users are overestimated while the one-vehicle households are underestimated. Hence, for simulation purposes, one can manually assign a portion of the predicted zero-vehicle and two-vehicle users as one-vehicle users. Figure 4.2 shows the comparison between the original predicted share and the adjusted simulated share. The conversion factor is computed using the sample shares and the shares predicted by the censored Poisson model. Specifically, the proportion of the zero-vehicle users converted to one-vehicle users is $1 - \rho\_(veh = 0, desired)/\rho\_(veh = 0, predicted)$ = 91.59% while that for two-vehicle users is $1 - \rho\_(veh = 2, desired)/\rho\_(veh = 2, predicted)$ = 28.40%. It can be seen that the sample shares are well reproduced.

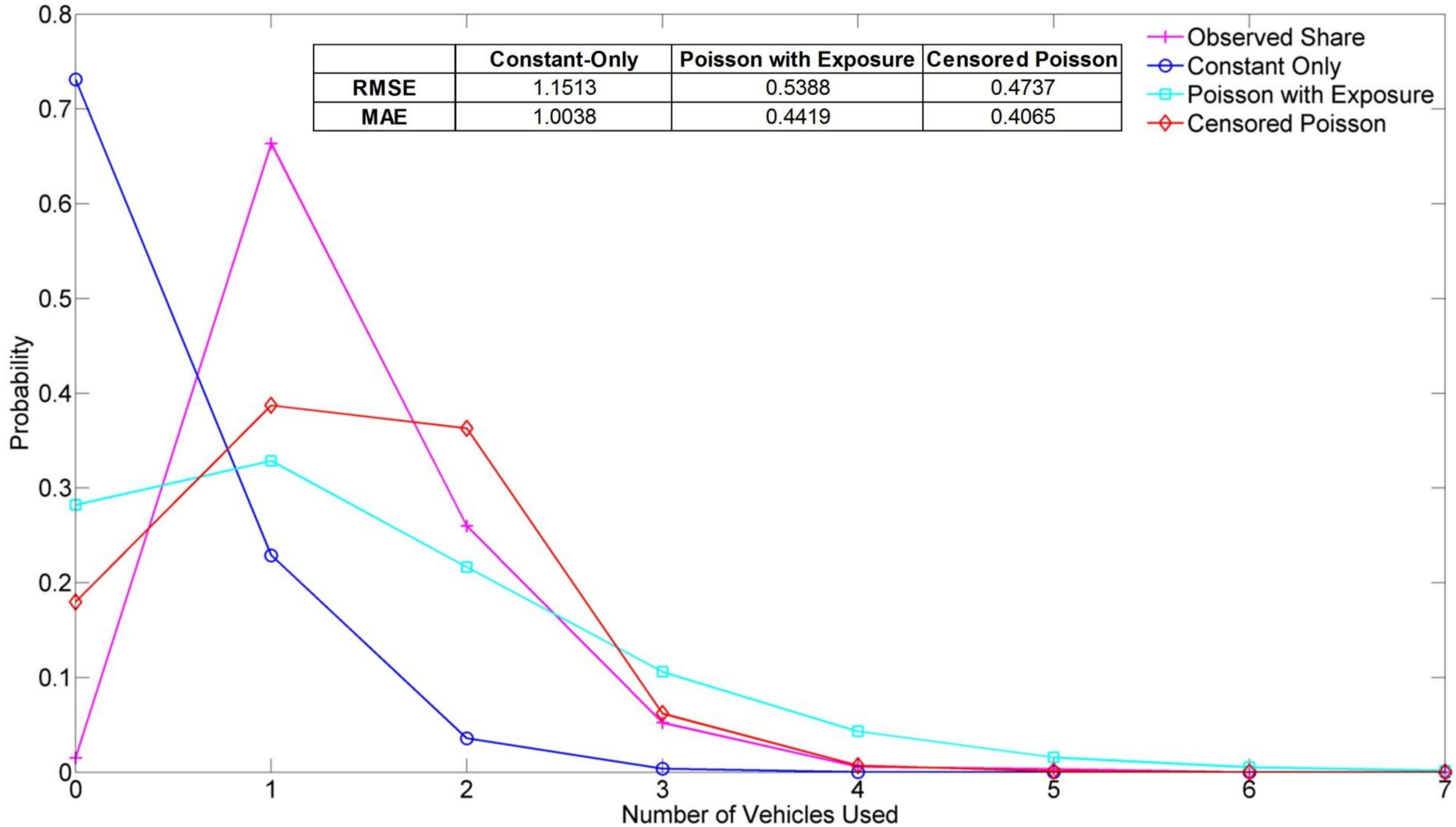

Figure 4.1 Predicted Shares for the Two Regression Models

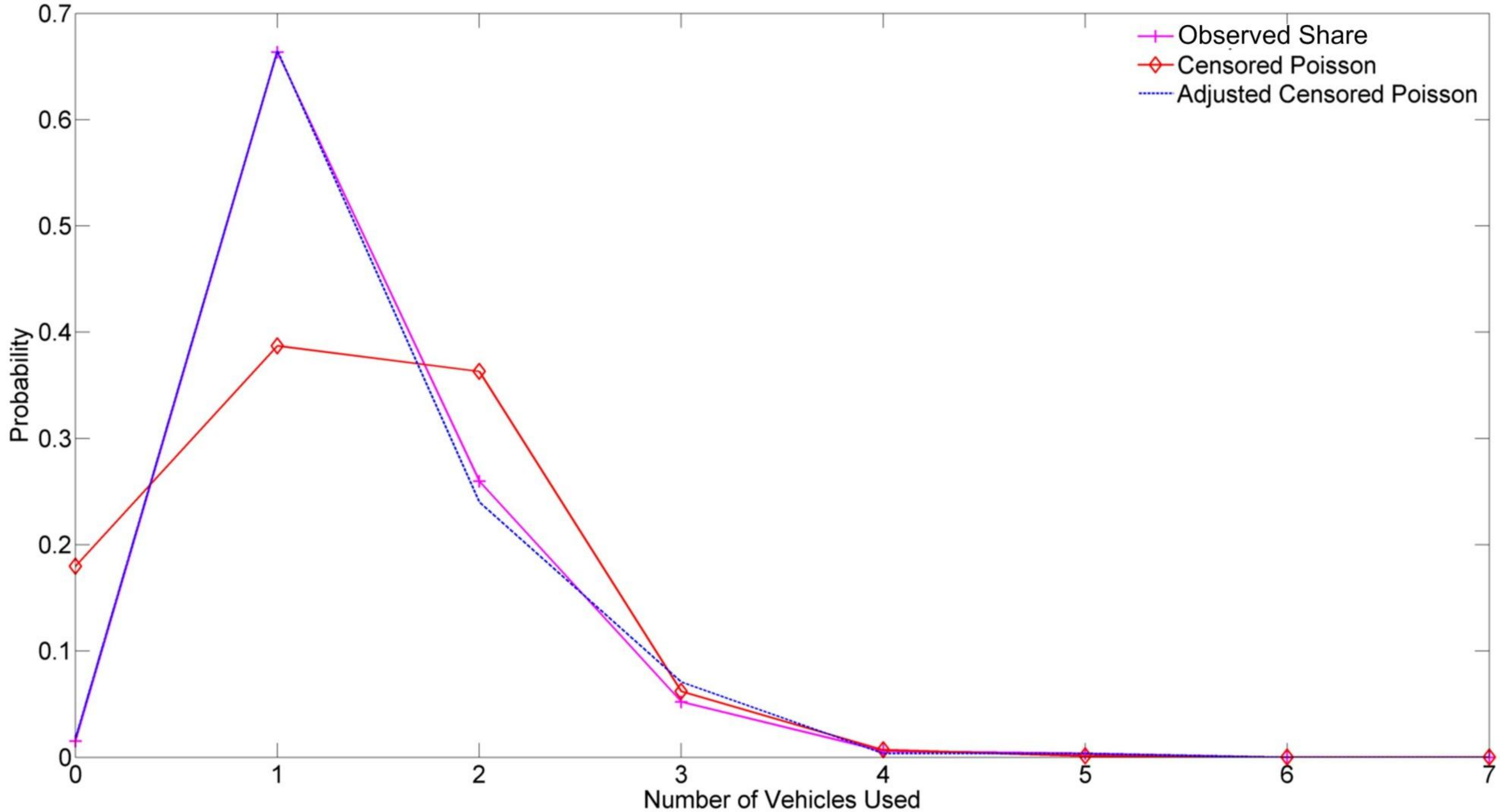

Figure 4.2 The Simulated Share for the Entire Sample

4.6 CONCLUSIONS AND FUTURE DIRECTIONS

This paper presents two variants of the regular Poisson regression model for the vehicle usage choice based on a post-storm survey for Hurricane Ivan: the Poisson model with exposure and right-censored Poisson regression. The two models explicitly consider the fact that the number of vehicles used for evacuation cannot exceed the number of vehicles owned by the household, which the ordered-response models fail to accommodate.

Between the two models, the right-censored Poisson model is preferred. It has better measures of fit and superior predictive power. Furthermore, by construction, it provides zero probabilities for numbers of vehicles used exceeding the number of vehicles owned. Therefore, it should be chosen for developing individual predictions of vehicle usage for simulation purposes. The model with the adjustment described earlier is being used by the authors for evacuation demand simulation.

Since the right-censored Poisson model is the preferred model, the conclusions with respect to the hypotheses are drawn using this model.

1. *Households that travel longer distance are more likely to use fewer vehicles*. The regression analysis supports this hypothesis. Households may prefer to stay together during the evacuation and/or multiple drivers may be needed per vehicle.

2. *Households who evacuate late are statistically more likely to use fewer vehicles*. This hypothesis is supported by the PR-C model. Generally, longer stay duration leads to fewer vehicles used, possibly because of congestion concerns.

3. *Households with previous hurricane experience are more likely to use a greater number of vehicles*. This hypothesis is supported. Households with previous hurricane experience may be more prepared, want to take more personal items, and/or may be more likely to want to protect their vehicles, especially if they experienced vehicle damage in previous hurricanes.

4. *The number of household members between 18 and 80 is positively related to the number of vehicles taken on the evacuation*. This hypothesis is supported. Adults of these ages may be more likely than teenagers or the elderly to have driving responsibilities during stressful events, such as evacuations.

5. *Household income is positively related to the number of household evacuation vehicles chosen*. This hypothesis was not supported by the multivariable models where income is insignificant. Related to vehicle ownership, the effect of income is partly captured via the explicit treatment of vehicle ownership constraints upon the vehicle usage choice. However, the Pearson correlation calculation for our sample reveals a positive linear correlation with the number of vehicles used, consistent with previous findings (Dow and Cutter, 2002b; Lindell et al., 2011).

6. *Pet-owning households are statistically more likely to evacuate with more vehicles than households without pets*. This hypothesis is supported, possibly due to the pet's needs.

7. *The households living farther from the coast are less likely to take more vehicles that those living close to the coast.* This hypothesis is not supported by the multivariable modeling. However, a negative Spearman correlation that supports the hypothesis is obtained in the descriptive analysis.

4.6.1 Future Directions

Though this paper identifies contributing factors to vehicle usage choice in hurricane evacuation, the underlying motivations for the vehicle usage choice are still unclear. For example, households taking two or more cars may have job responsibilities that require one member to return sooner than others or they simply want the flexibility to allow one member to return to cleanup while others stay with children. Hence, one future direction is to investigate the motivations for taking multiple vehicles. Additionally, the methodology used in this paper considers the ordinal nature of the vehicles. However, the vehicle types (e.g., SUV, sedan) are not included. Households taking more than two cars may use large vehicles to carry possessions. Thus, another possible future direction is to model vehicle characteristics and the number of vehicles simultaneously.

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CHAPTER 5 PRE-EVACUATION ACTIVITIES FOR HURRICANE EVACUATION: AN ANALYSIS OF BEHAVIORAL INTENTIONS FROM MIAMI BEACH, FLORIDA

This chapter presents a paper that has been accepted for presentation in the 93rd Annual Meeting of the Transportation Research Board, 2014. It was co-authored by Weihao Yin, Pamela Murray-Tuite, Satish Ukkusuri and Hugh Gladwin.

ABSTRACT

Hurricane evacuation demand studies typically focus on ultimate evacuation trips, however, households often first undertake activities to prepare their homes and themselves for the evacuation. These activities delay the evacuation process but are understudied. This paper presents a descriptive analysis of and econometric models for households' pre-evacuation activities based on behavioral intention data collected for Miami Beach, Florida. The descriptive analysis shows that shopping - particularly food, gasoline, medicine, and cash withdrawal - accounts for the majority of preparation activities, highlighting the importance of maintaining a supply of these items. More than 90% of the tours are conducted by driving, emphasizing the need to incorporate pre-evacuation activity travel into simulation studies. Households perform their preparation activities early in a temporally concentrated manner and generally make the tours during daylight. Households with college graduates, larger households, and households who drive their own vehicles are more likely to engage in activities that require travel. The number of household members older than 64 has a negative impact upon engaging in out-of-home activities. An action day choice model for the first tour suggests that households are more likely to buy medicine early but are more likely to pick up friends/relatives late. Households evacuating late are more likely to conduct their activities late. Households with multiple tours tend to make their first tour early. About 10% of households chain their single activity chains with their ultimate evacuation trips. The outcomes of this paper can be used in demand generation for traffic simulations.

Keywords: evacuation; hurricane; demand; activities

5.1 INTRODUCTION

Transportation planning for hurricane evacuations largely depends on simulating the interaction between evacuation traffic and transportation infrastructure. The simulation output's quality depends on the input's accuracy, including the demand representation, which can be derived from studies of evacuation behavioral patterns and households' trip-related decisions. Most previous studies related to hurricane evacuation demand focus on the ultimate evacuation trips, since they constitute a large proportion of the demand, and households' logistical decisions regarding the ultimate trips. Wu et al. (2012) summarize major findings regarding the evacuation departure time, route, vehicle usage, and evacuation distance and destination choices. In addition to the ultimate trip, evacuation-related demand includes trips derived from pre-evacuation preparation activities. Pre-evacuation activities can span several hours or even days and often involve multiple trips between various locations (Wolshon et al., 2009). This travel derived from mobilization activities often occurs on local transportation infrastructure which can inhibit evacuating traffic's progress toward designated evacuation routes. The delay caused by pre-evacuation trips is neither well understood nor well represented in hurricane evacuation models (Lindell et al., 2005). Ignoring these trips may lead to underestimated evacuation time estimates (Wilmot and Mei, 2004) as well as incomplete understanding of travel needs during an evacuation period. The objective of this paper is to develop models and provide behavioral findings regarding hurricane pre-evacuation activity travel that can address questions about types of activities and activity scheduling and provide pointers to representing this demand in simulation studies.

In the no-notice evacuation context, activities before the ultimate evacuation trip, such as gathering family members or meeting at home, have begun to be investigated (Liu et al., 2012, accepted-b; Ma et al., 2009; Murray-Tuite and Mahmassani, 2003) and integrated into evacuation simulations (Lin et al., 2009; Liu et al., accepted-a; Murray-Tuite and Mahmassani, 2004). However, the pre-evacuation trips for hurricanes are infrequently investigated, despite their importance to the hurricane evacuation simulation models' accuracies. Some early models, such as the WITNESS model (Farahmand, 1997) and MASSEVAC

(Hobeika and Kim, 1998), over-simplify pre-evacuation trips by assuming all households share the same temporal evacuation delay and behavior. These models only considered mobilization activities through a temporal loading distribution, which assigned evacuees' departure times.

Noltenius and Ralston (2010) are among the few who studied pre-evacuation trip-making behavior for hurricanes. They conducted a survey for Key West, Florida after Hurricane Wilma struck in October, 2005. They found that pre-evacuation trips show a dispersal of origins and destinations resulting in traffic that flows in many directions, not just toward ultimate evacuation destinations (Noltenius, 2008). They also examined trips chained with the ultimate departure and found households made several stops before leaving. Some trips used the major evacuation route and contributed to the traffic congestion (Noltenius and Ralston, 2010). However, their study is largely a descriptive analysis and does not strictly examine links among activity participation decisions, evacuation decisions (e.g., timing for ultimate evacuation trips), and socio-economic factors.

This study builds on the limited existing literature by (1) descriptively examining the pre-evacuation activity travel behavior from the perspective of an activity-based approach, based on a behavioral intention survey conducted in Miami Beach and (2) statistically modeling evacuating households' activity participation and scheduling decisions. The analysis provides insights into the characteristics associated with the pre-evacuation activities. Activity-based models are widely used for regular planning purposes (Pendyala and Ye, 2005), such as the modeling system developed by Bhat et al. (2000; 2001; 2002). However, evacuation activity travel behavior is different from that under normal conditions. Regular planning activity travel models generally focus on a 24-hour planning horizon while evacuation preparation activities usually span days and involve activities that allow evacuees to effectively plan for evacuation. In addition, the activities tend to performed in a more condensed manner due to the evacuation needs.

The remainder of this paper is organized as follows. The next section provides an overview of the survey data and a descriptive analysis of the households' pre-evacuation activity participation behavior. Then we statistically examine the effects of possible contributing factors to the households' pre-evacuation activity-travel choices. The last section summarizes the behavioral findings, discusses implications for generating demand for traffic simulation, and identifies future research directions.

5.2 OVERVIEW OF THE DATA AND DESCRIPTIVE STATISTICAL ANALYSIS

This study's data come from a household survey conducted in Miami Beach, Florida for a hypothetical category-four hurricane forecast to make landfall early Thursday morning. Evacuation notices are issued on Saturday at 10 am and people in evacuation zones should evacuate by 10 am Wednesday, which gives households a five-day response period. Telephone interviews were conducted with 707 households, and 606 households indicated they would evacuate. Households were asked for details regarding the activities they would engage in before they embark on the ultimate evacuation trip, including the activity's purpose, location, and action time (i.e., day and time range); travel mode; and whether the activity is chained with the ultimate trip. In addition to pre-evacuation activities, the survey also included questions about the households' socio-demographics and evacuation decisions (e.g., evacuation departure timing, accommodation type at the destination).

Through open ended questions, the survey requested up to five of the most important, travel-involving activities that respondents would participate in prior to departing for their ultimate evacuation destinations. However, most respondents included activities that do not involve travel such as "close windows and shutters." The reported activity information was reviewed to extract details for subsequent analysis using an activity-based approach. The out-of-home activities reported to be performed on the same day and same time range (i.e., early morning, morning, afternoon, and night) using the same mode of transportation are assumed to be performed in one tour - a circuit that begins and ends at the same location (Bhat and Singh, 2000). A tour is usually composed of several stops where the specific activities are pursued. This assumption stems from the consideration that households would minimize the number of tours especially in an evacuation. In addition, as later analysis will demonstrate, the activities performed in a tour generally have similar characteristics. Most households reported that they would shop for essential items, such as food, gas, and medicine, and withdraw cash in a tour. Therefore, there is reason to believe that households would group these stops in one tour. In this way, the original responses are organized into a tour-based representation of the pre-evacuation activity travel throughout the entire planning horizon.

After eliminating observations with missing values for preferred evacuation departure time, activity types and activity scheduling information, such as action day and time range, a sample of 462 evacuating households was assembled for subsequent analysis. The resulting dataset's demographics are similar to those reported for the Miami Beach area by the Department of Planning and Zoning (2011) of Miami-Dade in terms of Hispanic ethnicity (38.7% (Sample) vs. 36.4% (Census)) and average household income ($30,000 to $50,000 (Sample) vs. $43,957 (Census)), though the average household size is somewhat higher (2.25 (Sample) vs. 1.87 (Census)).

5.3 DESCRIPTIVE ANALYSIS

The descriptive analysis pertains to several dimensions of pre-evacuation activity travel behavior including the tour characteristics (number of tours and stops), the specific activities, mode choice, scheduling choices, and stop locations.

5.3.1 Tour Characteristics, Activity Type and Sequence

The sample contains 235 households that reported at least one tour. The remaining 227 households indicated they would only perform in-home activities before departure. Most households (91%, 214 out of 235) would make a single tour for their evacuation preparations and we inferred that 19 households would make two tours. Only two households would make three one-stop tours and one would evacuate on

Tuesday and the other on Wednesday. Among the single-tour households, approximately 78% would make one stop, which might serve two purposes as shown in Table 5.2. As expected, the number of stops in a tour decreases as the number of tours increases. Among the 19 households making two tours, only two would make two stops on both tours. Note that the households' complete activity travel information is not available. Therefore, households may perform tours in addition to the ones analyzed here to follow their daily routines. The tours reported might be considered as the additional tours made for evacuation preparations.

Table 5.1 shows the distribution of activity combinations by number of tours and Table 5.2 describes the distribution of the activity sequences performed at the stops. Here, the activities are described by specific purposes (e.g., food or gas purchase) instead of general categories like shopping since evacuation preparation activities are largely shopping activities.

Table 5.1 Activity Combinations by Number of Tours

Activity Combination	1 Tour	2 Tours	3 Tours	Total
CASH	14	0	0	14
CASH,FOOD	4	0	0	4
CASH,MEDICINE	1	0	0	1
FOOD	40	0	0	40
FOOD,CASH,GAS	3	1 (20%)	1 (20%)	5
FOOD,GAS,MEDICINE	0	1	0	1
FOOD,MEDICINE	10 (67%)	5 (33%)	0	15
FOOD,SUPPLIES[a]	6 (86%)	1 (14%)	0	7
GAS	58	0	0	58
GAS,CASH	10 (83%)	2 (17%)	0	12
GAS,CASH,SUPPLIES	1	0	0	1
GAS,FOOD	23 (88%)	3 (12%)	0	26
GAS,FOOD,SUPPLIES,MEDICINE	0	1 (50%)	1 (50%)	2
GAS,MEDICINE	4	0	0	4
GAS,MEDICINE,CASH,FOOD	0	1	0	1
GAS,SUPPLIES	5 (83%)	1 (17%)	0	6
MEDICINE	19	0	0	19
PICKING-UP[b]	8	0	0	8
PICKING-UP, GAS,CASH	0	1	0	1
PICKING-UP, MEDICINE	0	1	0	1
PICKING-UP,FOOD	0	1	0	1
PICKING-UP,GAS	2	0	0	2
SUPPLIES	6	0	0	6
Total	214	19	2	235

a. “Supplies” is the word used in the survey response.
b. “Picking-up” refers to picking up family members and friends.

Table 5.2 Activity Types at Tour Stops

	1 Tour			2 Tours					3 Tours		
	Tour 1			Tour 1			Tour 2		Tour 1	Tour 2	Tour 3
	Stop 1	Stop 2	Stop 3	Stop 1	Stop 2	Stop 3	Stop 1	Stop 2	Stop 1	Stop 1	Stop 1
CASH	18 (8%)	9 (19%)	1 (50%)	2 (11%)	1 (33%)	0	2 (11%)	0	0	0	1 (50%)
FOOD	54 (25%)	13 (27%)	0	5 (26%)	1 (33%)	0	6 (32%)	1 (50%)	1 (50%)	0	0
GAS	79 (37%)	13 (27%)	0	6 (32%)	0	0	3 (16%)	1 (50%)	1 (50%)	1 (50%)	0
MEDICINE	21 (10%)	10 (21%)	0	5 (26%)	1 (33%)	0	3 (16%)	0	0	0	0
SUPPLIES	8 (4%)	3 (6%)	1 (50%)	0	0	1 (100%)	2 (11%)	0	0	1 (50%)	0
PICKING-UP	10 (5%)	0	0	0	0	0	3 (16%)	0	0	0	0
FOOD+CASH	3 (1%)	0	0	0	0	0	0	0	0	0	0
FOOD+GAS	9 (4%)	0	0	1 (5%)	0	0	0	0	0	0	0
FOOD+MEDICINE	3 (1%)	0	0	0	0	0	0	0	0	0	1 (50%)
FOOD+SUPPLIES	4 (2%)	0	0	0	0	0	0	0	0	0	0
GAS+CASH	3 (1%)	0	0	0	0	0	0	0	0	0	0
SUPPLIES+GAS	2 (1%)	0	0	0	0	0	0	0	0	0	0
Total	214	48	2	19	3	1	19	2	2	2	2

Table 5.3 The Mode Choice, Action Day and Action Time Range of the Tours

	1 Tour	2 Tours		3 Tours		
Mode Choice	Tour 1	Tour 1	Tour 2	Tour 1	Tour 2	Tour 3
CAR	185 (86%)	17 (89%)	19 (100%)	2 (100%)	1 (50%)	2 (100%)
WALK	12 (6%)	2 (11%)	0	0	1 (50%)	0
TRANSIT	17 (8%)	0	0	0	0	0
Action Day						
1 (Sat.)	63 (29%)	9 (47%)	1 (5%)	1 (50%)	0	0
2 (Sun.)	36 (17%)	8 (42%)	8 (42%)	1 (50%)	1 (50%)	0
3 (Mon.)	51 (24%)	1 (5%)	3 (16%)	0	1 (50%)	2 (100%)
4 (Tue.)	42 (20%)	1 (5%)	6 (32%)	0	0	0
5 (Wed.)	22 (10%)	0	1 (5%)	0	0	0
Action Time Range						
Early Morning (12:00 am ~ 6: 00 am)	2 (1%)	0	0	0	0	0
Morning (6:00 am ~ 12: 00 pm)	163 (76%)	15 (79%)	11 (58%)	2 (100%)	1 (50%)	0
Afternoon (12:00 pm ~ 6: 00 pm)	39 (18%)	3 (16%)	8 (42%)	0	1 (50%)	1 (50%)
Night (6:00 pm ~ 12: 00 am)	10 (5%)	1 (5%)	0	0	0	1 (50%)
Total	214 (100%)	19 (100%)	19 (100%)	2 (100%)	2 (100%)	2 (100%)

Most households perform their preparation activities in one tour. Only three households reported four activities, which would be performed in multiple tours. When households intend to pick up friends or relatives and buy medicine or food, they make separate tours. Activities may be under-reported. For example, 58 households report only one activity, fueling their vehicles, but in reality, may engage in other activities.

Food or gas purchases are the most common activity type at stop 1 regardless of the number of tours made. Buying medicine and withdrawing cash following the purchase of food or gas are also commonly reported. Only 13 households reported they would pick up friends and/or relatives who may rely on respondents' vehicles for evacuation as suggested by Wu et al. (Wu et al., 2012). If the first stop serves two purposes, households making only one tour would not make additional stops. In terms of the activity sequence, many different permutations were reported, which is understandable since the activities reported are all common and their sequence is subject to personal preferences.

5.3.2 Tour Travel Mode

Three modes were reported: driving, taking transit, and walking. Table 5.3 provides the distribution of travel modes by number of tours. Driving is the dominant mode, underscoring the importance of modeling the travel derived from these pre-evacuation activities since the vehicular traffic would exert additional pressure on the local transportation network. Walking and transit are also chosen by some single-tour households; possibly, households choose stores close to their homes to save time. Among the 13 cases of picking-up activities, driving was chosen by 12 while only one would use transit.

5.3.3 Tour Scheduling

Tour scheduling refers to the day and time households would perform their tours. Households have different planning horizons for their pre-evacuation activities due to their varied evacuation departure times. The planning horizon is the temporal duration from 12:00 AM Saturday[2] (10 hours prior to evacuation notice) until a household's evacuation departure time. Households that leave early perform activities in a relatively short period of time, while those leaving late have more scheduling options. Table 5.3 shows the distribution of the action days by number of tours.

More households would perform their preparation activities early, indicated by the decreasing percentage for the first tour as hurricane landfall approaches. Approximately 70% of the households indicated they would perform their first tour in the first three days if they have one tour. For those making two tours, almost 90% would perform the tours in the first two days while both three-tour households perform the first tour in the first two days. This suggests that households would like to start the evacuation preparation early, which allows them more time to purchase necessary items and thus minimizes the risk of forgetting essential items. More than 75% of the households (16 out of 21) who would make multiple tours perform the second tour on the same day of or the day following the day of their first tour. Only four households would wait two days until their second tours and one household would wait three days until the second tour. This suggests that most households prefer to perform their out-of-home preparation activities in a temporally concentrated manner. Other factors, such as the activity types and the length of the planning horizon, are likely to contribute to the tour scheduling and are investigated in later multi-variable statistical analysis.

Due to the survey design, the respondents indicated time ranges such as "Morning" and "Afternoon" for their action time instead of precise times. Table 5.3 documents the distribution of the action time range by number of tours.

[2] A few respondents indicated that they would evacuate prior to the evacuation notice. The start of the planning horizon was selected to capture all evacuees.

As expected, households would perform the majority of the tours during daylight when shops are open. Regardless of the number of tours or tour day, approximately 80% of the first tours occur in the morning. The time ranges for the second tours seem to be about evenly split between morning and afternoon for households indicating multiple tours. However, the reported preferred action time may change in an actual evacuation and generally would be subject to the constraints of daily routine.

5.3.4 Activity Chaining with Evacuation Trip

In the dataset, 20 households indicated they would chain their single activity chain with their ultimate evacuation trip. About half of these households (9 out of 20) would evacuate on the last two days. This suggests that the households that would evacuate late tend to chain their activities with their ultimate evacuation. Only one household would chain the second tour, picking-up a friend, with the ultimate evacuation trip.

5.3.5 Tour Stop Locations

About half of the respondents provided addresses and location information for their activities that could be used for geocoding and spatial analysis. The stop locations are geocoded using ArcGIS. Table 5.4 shows the distances between stops and home by activity type.

Table 5.4 The Descriptive Statistics of Distance to Home of Tour Stops by Activity Type (In Miles)

	Num Obs	Mean	Std. Dev.	Min.	Max.
CASH	17	0.81	0.81	0.13	3.33
FOOD	49	0.80	1.12	0.05	7.40
GAS	57	0.91	1.61	0.03	8.73
MEDICINE	27	1.07	1.61	0.01	7.58
SUPPLIES	10	1.38	2.43	0.07	7.48
PICKING-UP	5	1.63	1.54	0.74	4.35
FOOD+CASH	3	0.84	0.90	0.11	1.85
FOOD+GAS	8	1.03	0.98	0.08	3.32
FOOD+MEDICINE	4	1.11	0.93	0.07	2.13
FOOD+SUPPLIES	4	0.45	0.50	0.03	1.17
GAS+CASH	3	1.00	0.74	0.49	1.85
SUPPLIES+GAS	2	0.71	0.33	0.48	0.94
Total	189	0.84	1.26	0.03	8.73
1 mile = 1.6 km					

The stop locations are fairly close to respondents' homes, with less than 2 mile average distance. All pick-up locations were reported to be in Miami Beach. Households generally travel farther for supplies and picking-up activities. Some households (9 out of 235) travel relatively longer distances to major shopping locations located outside Miami Beach to buy food, gas, medicine, or supplies. The distance between the first stop and second stop for multi-stop tours has a mean of 0.90 miles with a standard deviation of 1.81 miles, suggesting that the stops are generally close to each other.

5.4 BEHAVIORAL MODELING FOR PRE-EVACUATION ACTIVITIES

Quantitative assessment of the effects of household characteristics and other relevant evacuation decisions on the pre-evacuation activity participation behavior facilitates a detailed demand representation and subsequent predictive analysis for hurricane evacuation simulations. Two decisions are investigated further. First, the decision to engage in out-of-home activities (or not) is modeled using a binary logit model. An ordered logit model was developed using the number of tours as the dependent variable; however, due to the limited number of multi-tour households, the validity of the ordered logit specification cannot be verified using Brant's test for the parallel regression assumption suggested by Greene and Hensher (2010). Therefore, the binary choice specification for whether to engage in out-of-home activities is adopted.

Households' choices of engaging in specific activities (e.g., buying food) listed in Table 5.1 are not modeled econometrically due to limited numbers of cases for some activity combinations. However, the activity combinations and sequences can be simulated using the distributions described in Table 5.1 and Table 5.2 as discussed later for demand generation for traffic simulation.

Second, the action day choice for the first tour is examined using a discrete hazard-based duration model. Ideally, the action timing expressed in minutes would be modeled as in Bhat et al. (2002) for regular planning, if that level of post-storm data were available. The temporal resolution for the action timing modeling adopted here is day instead of time ranges of specific days. The time ranges are not econometrically modeled because the time range is not an accurate measuring unit that precisely describes time. The time ranges for the intended activity action time are dominantly morning and afternoon and the split between morning and afternoon exhibits limited variation by the number of tours and the day of the tours. The distribution depicted in Table 5.3 serves reasonably well for generating specific action timing ranges for evacuation demand modeling. In addition, due to insufficient observations (21 households making multiple tours) the estimation of separate models for action days for the second and third tours is not possible. However, the descriptive analysis shows that the temporal difference between the second tour and the first tour is generally less than one day for the majority of households, which serves as the behavioral foundation for demand simulation purposes. Hence, this paper only models the action day choice for the first tour.

The households' socio-demographic characteristics are investigated during the process of model construction. The procedure proposed by Hosmer and Lemeshow (2000) is followed by first constructing the uni-variable models to examine the effects of individual covariates. Then, a full model that contains all covariates that bear practical and individual statistical significance is constructed and the insignificant covariates are then removed based on likelihood ratio tests.

5.4.1 Out-of-Home Activity Participation Choice

As mentioned above, 235 households reported at least one tour and 227 households would only stay home before departure. Since whether a household would engage in any activity that requires travel is a dichotomous response, a binary logit model is used to investigate this decision. Let random variable Y take the value "1" if the household participates in at least one out-of-home activity before evacuation departure and "0" otherwise. Then the binary logit model specifies that the probability that a household would participate in at least one out-of-home activity is given by Eq.(5.1) (Greene, 2012),

$$\text{Prob}(Y = 1|\mathbf{x}) = \frac{\exp(\mathbf{x}'\boldsymbol{\beta})}{1 + \exp(\mathbf{x}'\boldsymbol{\beta})} \tag{5.1}$$

where $\mathbf{x}$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is the coefficient vector. The model parameters are estimated using STATA by maximum likelihood estimation by treating each observation as a single draw from a Bernoulli distribution with the probability specified in Eq.(5.1).

The available covariates fall into two categories: evacuation decisions and household characteristics as listed in Table 5.5. Since existing literature does not provide guidance for the selection of the variables for these particular decisions, the selection is led by the univariable odds ratio analysis.

5.4.1.1 Association between the Covariates and the Out-of-Home Activity Participation Choice

The households' mode choice for evacuation has a statistically significant impact upon the out-of-home activity participation choice. Driving their own vehicles (73.3%) is the dominant evacuation mode, consistent with previous findings such as (Wu et al., 2012). Households that would evacuate in their own vehicles are more likely to engage in out-of-home activities while households that would evacuate using transit, carpools, or other modes are much less likely to perform activities that require travel. This is possibly because their lack of mobility increases the difficulty of shopping and performing other out-of-home activities.

Some socio-demographic characteristics are also statistically significant. Households with relatively low income and limited education attainment are more likely to perform only in-home activities. The odds ratios for households with income less than $10,000 and for those with less than high-school education suggest that these households are almost twice as likely to perform only in-home activities. As expected, households with relatively better economic conditions are more likely to engage in out-of-home activities, evidenced by the larger-than-unity odds ratio for the single family home dwellers. In addition, a larger household is more likely to engage in out-of-home activities possibly because they need more supplies for their evacuation trip. More children under 12 years old and more adults between 19 and 64 years old lead to increasing likelihood of engaging in out-of-home activities, which may be because the children have more needs and households with more adults have the personnel to perform out-of-home activities. This is further illustrated by the less-than-unity odds ratio of the number of household members over 64 years old. One more over-64-years member leads to a 31% (100%×(1-0.697)) decrease in odds to perform any out-of-home activity possibly due to mobility constraints faced by senior citizens.

Table 5.5 Association between Individual Covariates and the Decision to Perform Out-of-home Activities

Variables	Description	Sample Mean	Crude Odds	Adjusted Odds	Likelihood Effect
Evacuation Decisions					
[dur]	Duration in hours until departure for evacuation destination	77.19	1.002 (0.003)	0.997 (0.003)	
[friend]	Evacuation destination is a friend/relative's home	0.671	1.189 (0.249)	0.968 (0.500)	
[hotl]	Evacuation destination is a hotel	0.243	0.964 (0.221)	0.821 (0.453)	
[shelter]	Evacuation destination is a public shelter	0.084	0.664 (0.237)	ref. cat.	
[localdest]	Evacuation destination is in Miami-Dade area	0.361	0.895 (0.173)	0.927 (0.226)	
[owncar]	The household's evacuation mode is driving their own car	0.733	2.952*** (0.657)	2.666** (1.278)	⇑
[passenger]	The household's evacuation mode is being passengers	0.099	0.431** (0.142)	1.139 (0.652)	⇓
[transit]	The household's evacuation mode is transit	0.054	0.435** (0.191)	0.941 (0.638)	⇓
[evacbus]	The household's evacuation mode is evacuation bus	0.043	0.398* (0.198)	0.698 (0.559)	⇓
[othmode]	The household's evacuation mode is other mode	0.069	0.414** (0.162)	ref. cat.	⇓
Socio-Demographic Characteristics					
[hispn]	The household respondent is Hispanic	0.387	1.073 (0.205)	1.151 (0.303)	
[incu10k]	The household income is less than 10,000 USD	0.151	0.596** (0.157)	1.256 (0.567)	⇓
[inc1020k]	The household income is between 10,000 USD and 20,000 USD	0.091	1.321 (0.431)	2.362 (1.166)	
[inc2030k]	The household income is between 20,000 USD and 30,000 USD	0.372	0.946 (0.182)	1.041 (0.315)	
[inc3050k]	The household income is between 30,000 USD and 50,000 USD	0.071	1.531 (0.565)	1.460 (0.649)	
[inc5080k]	The household income is between 50,000 USD and 80,000 USD	0.084	1.139 (0.382)	0.993 (0.430)	
[inco80k]	The household income is more than 80,000 USD	0.229	1.107 (0.245)	ref. cat.	
[lthigh]	The household's highest education level is less than high school	0.091	0.450** (0.154)	0.628 (0.301)	⇓
[highgrad]	The household's highest education level is high school	0.132	0.997 (0.274)	1.108 (0.426)	
[ltcol]	The household's highest education level is less than college	0.067	0.679 (0.256)	0.774 (0.352)	
[colgrad]	The household's highest education level is college graduate	0.398	1.406* (0.268)	1.372 (0.365)	⇑
[pgrad]	The household's highest education level is post graduate	0.311	1.031 (0.207)	ref. cat.	
[rent]	The household lives in a rented property	0.346	0.753 (0.147)	0.956 (0.284)	
[apt]	The household lives in an apartment	0.311	0.746 (0.150)	0.969 (0.354)	
[condo]	The household lives in a condo	0.406	0.943 (0.178)	0.938 (0.271)	
[duplex]	The household lives in a duplex home	0.008	2.922 (3.385)	3.858 (4.969)	
[sfh]	The household lives in a single family home	0.273	1.415* (0.298)	ref. cat.	⇑
[hhsize]	The household size	2.259	1.271*** (0.092)	1.157 (0.192)	⇑
[chldu12]	The number of children under 12 years old	0.242	1.397** (0.025)	0.979 (0.213)	⇑
[chld1218]	The number of children between 12 to 18 years old	0.149	1.304 (0.253)	/	
[adlt1964]	The number of adults between 19 to 64 years old	1.184	1.416*** (0.120)	1.107 (0.324)	⇑
[over64]	The number of household member over 64 years old	0.683	0.697** (0.085)	0.736** (0.107)	⇓
[preevac]	The household has previous evacuation experience	0.595	1.388* (0.264)	1.240 (0.281)	⇑

The covariates that pass the 0.25 significance threshold (2000) are considered in the following multi-variable modeling. The empirical results of the final model are shown in Table 5.6.

Table 5.6 Estimation Results of the Model for Out-of-Home Activity Participation Choice

Variable	Coefficient	Average Marginal Effect
Whether household has a college graduate	0.325* (0.198)	0.075* (0.046)
Household size	0.136* (0.0732)	0.032* (0.0167)
The number of household members older than 64	-0.273** (0.126)	-0.063** (0 .028)
The evacuation travel mode is driving their own car	0.919*** (0.231)	0.217*** (0.052)
Constant	-0.893*** (0.268)	
Number of Observations: 462, Log-Likelihood = -301.429, Outcome = 1 represents households performing at least one out-of-home activity. $\chi2$= 37.47 and P-value for chi-square test < 0.001 Pseudo R2 = 0.059; Area under ROC = 0.659 Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1		

The model is statistically significant as shown by the likelihood chi-square test whose null hypothesis that all coefficients are zero is rejected at the 0.001 significance level. The area under the Receiver Operating Characteristic (ROC) curve measures the models' discrimination capacity. is the value 0.659 suggests acceptable, although not excellent, explanatory power (2000).

Table 5.6 also shows the average partial effect, which supplements the coefficient estimates in the examination of individual covariates' effects. The parameters of the model generally do not equal the marginal effects due to the logit model's non-linear nature. To examine the individual covariates' effects upon the probability of performing any out-of-home activities, we consider the marginal effects, which depend on the specific covariate values. The marginal effects at every observation are evaluated and then averaged to derive the average partial effect (APE), which is favored by current practice (Greene, 2012).

Four variables show statistically significant effects upon the out-of-home activity participation choice. Households with college graduates are more likely to engage in activities that require travel. The APE indicates that having college graduates increases the probability of engaging in out-of-home activities by 0.08 with other variables held unchanged. Larger households are more likely to participate in out-of-home activities, evidenced by the positive APE suggesting one more person leads to an increase of the probability of participating in out-of-home activities by 0.032, possibly because large households require more evacuation related shopping activities. The number of people older than 64 has a negative impact upon engaging in out-of-home activities. One more household member older than 64 decreases the probability of participating in any out-of-home activity by 0.063 holding other variables constant. The households who choose to drive their own vehicles are more likely to participate in out-of-home activities. Though some households reported that they would not engage in any out-of-home activities, they may not actually stay home until they evacuate. A more practical interpretation might be that they would not make dedicated tours for evacuation preparation but they may still follow their daily routines.

5.4.2 Action Day Choice for the 1st Tour for Out-of-Home Activities

It is assumed that households have decided their evacuation departure times and they need to schedule their tours for pre-evacuation activities in the planning horizon determined by the evacuation time. Since the action day is a discrete time response, it is modeled via a discrete-time hazard-based survival model, defined as the conditional probability of making the first tour at a time point given that the tour has not been conducted in previous time steps. Discrete-time hazard-based survival models can be converted to standard models for dichotomous responses such as the standard logit model (2012) (Eq.(5.1)). Let y_{si} be an indicator for making the first tour at time *s* for household *i* and d_{1si}, d_{2si},…, d_{5si} are dummy variables for days from Saturday to Wednesday. Then the logit of the discrete-time hazard h_{si} is given by Eq.(5.2),

$$\text{logit}\{\text{Prob}(y_{si} = 1|\boldsymbol{d_{si}})\} = \alpha_1 + \alpha_2 d_{2si} + \alpha_3 d_{3si} + \alpha_4 d_{4si} + \alpha_5 d_{5si} + \mathbf{x}'\boldsymbol{\beta} \qquad (5.2)$$

where $\boldsymbol{d_{si}}$ is a column vector storing the five dummy variables d_{1si}, d_{2si},…, and d_{5si}, $\boldsymbol{\alpha}' = (\alpha_1, \dots, \alpha_5)$ is the coefficient vector for the baseline hazard, $\mathbf{x}$ is a vector of explanatory variables, and $\boldsymbol{\beta}$ is the coefficient vector for the explanatory variables.

Since dummy variables are used, this discrete-time hazard-based survival model has a non-parametric nature and the intercept represents Saturday. The model can be estimated using maximum likelihood estimation for a standard logit model should the dataset be expanded according to the procedure proposed by Rabe-Hesketh and Skrondal (2012). In general, each household should be represented by a row of data for each day the household could make the first tour. For example, if a household makes the first tour on day 3, this record should be expanded into three replications and an indicator variable signifies the actual day that the tour occurs.

A similar model-building procedure is used as for the out-of-home activity participation choice. Individual uni-variable models are constructed for all the covariates listed in Table 5.5 but only the length of the planning horizon, the tour's activity types, and the number of tours are statistically significant at the 0.25 level and used in the multi-variable modeling. The effects of socio-demographic characteristics are already captured by the types of activities the households decide to participate in, which have been included as covariates in the multi-variable model. The statistical insignificance of socio-demographic characteristics was observed in some of the activity scheduling models developed by Bhat et al. (2002) for regular planning purposes.

The estimation results for the action day choice model for making the first tour are shown in Table 5.7. Since the model formulation is converted to a standard logit specification, the measures of fit for standard logit models are equally applicable here. The overall high statistical significance of the model is evidenced by the likelihood chi-square test with a p-value less than 0.001. The area under the ROC curve is 0.799 for the model, which suggests excellent explanatory power (2000).

Table 5.7 Estimation Results for the Action Day Choice for Tour 1

Variable	Parameter Estimate
Baseline Hazard	
Dummy Variable for Day 2 (Sun.)	0.269 (0.257)
Dummy Variable for Day 3 (Mon.)	1.480*** (0.279)
Dummy Variable for Day 4 (Tue.)	2.725*** (0.359)
Dummy Variable for Day 5 (Wed.)	0
Explanatory Variables	
The length of planning horizon	-0.036*** (0.004)
Number of Tours to be performed	1.549*** (0.363)
One Stop in Tour 1 is purchase of medicine	0.482* (0.285)
One Stop in Tour 1 is picking-up people	-1.308** (0.514)
Constant	0.0859 (0.498)

The dummy variable for Day 5 predicts the occurrence of activity 1 perfectly and hence is removed from the regression model (13 observations).
Number of observations in the expanded dataset: 579. Log-Likelihood = -309.377. $\chi 2$= 143.0 and P-value for chi-square test < 0.001. Pseudo R2 = 0.1877; Area under ROC = 0.799
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
b. The length of the planning horizon in hours is calculated as the time duration from Saturday midnight to the selected evacuation departure time.

The action day for the first tour is statistically significant to the activity type and the households' selected evacuation times. If the first tour involves purchasing medicine, the odds ratio is estimated as exp(0.482) = 1.619 implying that the odds of the occurrence of the first tour in any given day in the horizon given that it has not already occurred are almost 1.6 times those of a first tour involving other types of activities, controlling for the other covariates. This suggests that households are more likely to buy medicine early, possibly due to concerns about limited supplies. If the households pick up relatives/friends in the first tour, they are more likely to conduct the tour late; the odds ratio of 0.27 (exp(-1.308)) suggests that the odds of making the first tour in any given day in the horizon given that it has not already occurred decrease by 73% for a first tour involving pick-up stops, holding other covariates constant. The length of the planning horizon has a negative effect upon the action day of first tour. The odds ratio for every one-hour increase in the planning horizon is computed as exp(-0.0359) = 0.965, implying that the odds of making the first tour in any given day in the horizon given that it has not already occurred decrease by approximately 4% for every one-hour increase in the length of the planning horizon, holding other covariates constant. Thus, households who evacuate late are more likely to conduct their pre-evacuation activities late, which may be ascribed to more timing choices due to a longer planning horizon. As expected, the number of tours has a positive effect upon the action day of the first tour; the odds ratio is estimated as exp(1.549) = 4.71 implying that an increase in number of tours substantially increases the odds of the first tour occurring on a given day given that it has not already occurred, controlling for the other covariates. This suggests that the households with multiple tours tend to make their first tour early possibly because it allows more time to make subsequent tours.

5.5 CONCLUSIONS AND FUTURE DIRECTIONS

This paper presents an analysis of the households' pre-evacuation activities for hurricane evacuation based on behavioral intention data collected for Miami Beach, Florida. Descriptive analysis offers insights into activity types of the tours, travel mode, and scheduling and activity locations in terms of travel distance from home and between tour stops. Econometric models then identify the contributing factors to the out-of-home activity participation choice and the action day choice of the first tour.

The descriptive analysis shows that shopping accounts for the dominant proportion of preparation activities. The specific items reported include food, gasoline, medicine, and withdrawal of cash. Thus, it is important to maintain a steady supply of these items or to increase these supplies before the evacuation.

In terms of tour making behavior, most households would make a single tour, but multiple tours are observed. More than 90% of the tours are conducted by driving, which highlights the importance of incorporating pre-evacuation activity travel into simulation studies. Since this traffic exerts additional pressure on the local transportation network, traffic management strategies might be needed on major roads and in areas where preparation activities concentrate. Furthermore, strategies implemented without considering pre-evacuation activities may hinder the overall evacuation process unless carefully timed.

The tours' action days indicate that households perform their preparation activities early, allowing them more time to make purchases and minimizing the risk of forgetting essential items. More than 75% of the households who would make multiple tours perform the second tour on the same day of or the day following their first tour. Households would generally make the tours during daylight, as expected; 80% of the first tours would be performed in the morning and the second tours are about evenly split between morning and afternoon for households indicating multiple tours. About 10% of the households chain their single activity chains with their ultimate evacuation trips. About half of these households would evacuate on the last two days. Thus, households that would evacuate late tend to chain their activities with their ultimate evacuation. The activity locations are fairly close to respondents' homes though households generally travel farther for supplies and picking-up activities. Only a few households travel longer distances to major shopping locations located outside Miami Beach. The close distance between the first and second stops suggests that the stops are generally close together.

Two decisions are investigated further. The participation in the activities that involve travel is investigated via a binary logit model; four variables are statistically significant. Households with college graduates, larger households, and households who drive their own vehicles are more likely to engage in activities that require travel. The number of people older than 64 has a negative impact upon engaging in out-of-home activities.

The action day for the first tour is examined using the discrete-time hazard-based survival model and is statistically significantly related to the activity type, household's selected evacuation time, and the number of tours. If the first tour involves purchasing medicine, the households are more likely to buy medicine early possibly due to concerns about limited supplies. If the households pick up relatives/friends in the first tour, they are more likely to conduct the tour late. Households who evacuate late are more likely to conduct their pre-evacuation activities late. Finally, households with multiple tours tend to make their first tour early.

The behavioral findings regarding the pre-evacuation activities can be used, in conjunction with models of other evacuation related decisions, to generate demand for traffic simulation applications and the authors are currently pursuing this in an agent-based demand simulation model. Once the activity planning horizon is calculated based on evacuation departure time determined by other behavioral models such as the one in (Hasan et al., 2013a), the generation and scheduling of the evacuation-related activities can be achieved via the distributions showed in the descriptive analysis and behavioral models in this paper. The out-of-home activity participation choice model determines whether a household would perform any out-of-home activities. Then the number of tours can be simulated using the descriptive distribution. The specific activities and their sequence can then be simulated based on the activity type distribution and the relationship between the number of tours and stops. The day for the first tour can then be based on the action day choice model and the time ranges can be simulated using the frequency distribution by number of tours. The background demand can be derived from traditional planning models.

5.5.1 Future Directions

Ideally, households' complete activity travel sequences over the entire evacuation planning horizon would be documented. However, it seems impractical to ask evacuees to keep a travel diary during an evacuation. Therefore, novel data collection methods are needed to obtain a complete travel record in order to fully model the pre-evacuation activities. In addition, if the hurricane characteristics are also available, the activity scheduling may be modeled from a dynamic perspective such as the one proposed by Gudishala and Wilmot (2012a).

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CHAPTER 6 THE SIMULATION MECHANISM AND IMPLEMENTATION OF THE AGENT-BASED DEMAND MODEL SYSTEM

This chapter presents a paper that is currently under peer review. It was co-authored by Weihao Yin and Pamela Murray-Tuite

ABSTRACT

This paper develops an agent-based travel demand model system for hurricane evacuation simulation, which is capable of generating the comprehensive household activity-travel plans. The system implements econometric and statistical models that represent travel and decision-making behavior throughout the evacuation process. The system considers six typical evacuation decisions: evacuate/stay, accommodation type choice, evacuation destination choice, mode choice, vehicle usage choice and departure time choice. It explicitly captures the shadow evacuation population. In addition, the model system captures the pre-evacuation preparation activities using an activity-based approach.

A demonstration study that predicts activity-travel patterns using model parameters estimated for the Miami-Dade area is discussed. The simulation results clearly indicate the model system produced the distribution of choice patterns that is consistent with sample observations and existing literature. The model system also identifies the proportion of the shadow evacuation population and their geographical extent. About 23% of the population outside the designated evacuation zone would evacuate. The shadow evacuation demand is mainly located within 5 km of the coastline. The output demand of the model system works with agent-based traffic simulation tools and conventional trip-based simulation tools.

Keywords: Agent-based Simulation; Travel Demand; Hurricane Evacuation

6.1 INTRODUCTION

Hurricane evacuation is a highly complex and dynamic process, which is generally modeled using simulation-based tools (Pel et al., 2012). Simulation abstractions of the evacuation process require accurate representations of evacuation demand, which is governed by many factors, such as hurricane trajectory, warning system, and household characteristics (Baker, 1991b; Gladwin et al., 2001; Murray-Tuite and Wolshon, 2013b; Urbina and Wolshon, 2003). This paper presents an agent-based model system that captures household evacuation travel decisions and converts them into activity plans.

During an evacuation, households encounter a series of related decisions: whether to evacuate, when, to where, and by which mode, among other decisions. These decisions lead to the ultimate evacuation trips which constitute a large proportion of the evacuation demand. However, the demand also includes trips derived from pre-evacuation preparation activities, which can span several hours or days (Wolshon et al., 2009). These activities generate local traffic that was ignored in most previous evacuation simulation studies, possibly due to data unavailability, yet this local traffic contributes to overall congestion. Therefore, pre-evacuation activity travel should be considered in the demand representation.

Agent-based modeling and simulation (ABMS) is a useful approach to represent this complicated decision-making process. ABMS employs autonomous agents that can interact with the artificial surrounding environment (North and Macal, 2007). An agent has a set of attributes and behavioral characteristics. The attributes define an agent's identity and the behavioral characteristics define what an agent does (North and Macal, 2007). When a household is modeled as an agent, typical attributes include household size, number of children, and number of seniors. Agents' behavioral features can include decision rules to select actions, adaptation capabilities to learn from experiences, perceptual capabilities to sense surroundings, and optional internal mechanisms to project decisions' potential consequences

(North and Macal, 2007). For evacuation decision modeling, the behavioral characteristics can be constructed using econometric models and other findings from evacuation behavioral studies.

The advantages of the ABMS framework over other approaches in evacuation modeling are threefold. First, the households have different characteristics which lead to different behaviors. Even if the households have identical characteristics, they may choose different actions due to unobserved taste variation (Train, 2002). The agent is a useful abstraction capable of handling such behavior, especially for capturing shadow evacuation, largely due to households' different perceptions of risk. However, an aggregate demand modeling technique, usually applied in trip-based simulation models, generally fails to recognize taste variation. Second, ABMS can capture the evacuation decisions and preparation activity travel in a consistent and integrated manner. Households, the agents, are the actual entities that make evacuation decisions and they are also the trip-makers that conduct pre-evacuation travel and the ultimate evacuation trips. In comparison, the analysis units of conventional trip-based simulation models are individual trips generated at the level of traffic analysis zones (TAZs). This discrepancy renders coherent modeling of decision-making and trip-making behavior difficult, if not impossible. Finally, agents can interact with the external environment, such as hurricane characteristics. The external environment abstraction in the ABMS framework allows incorporation of these aspects of the evacuation process. Therefore, the ABMS framework is particularly suitable for simulating households' behaviors and exploring emergent collective phenomena in evacuation (Zhang et al., 2009).

In prior evacuation ABMS studies, the agent assumes different appearances in different transport simulation applications. Some studies (e.g., those using the microscopic simulation package VISSIM) define agents as cars that follow a certain car-following logic (PTV, 2011). Adopting this convention, Chen et al. (2006) evaluated various evacuation scenarios for Florida Keys using VISSIM. They generated evacuation demand at the level of evacuation zones. Other studies that considered cars as agents focused on evacuation route choice. For example, Handford and Rogers (2011) considered agents' familiarity with local routes. Zhang et al. (2009) explicitly dealt with the risk-taking preference for evacuees in route choice by categorizing the households as "normal" and "greedy" agents in hurricane evacuation.

A few studies considered decision-making entities as agents, an alternative to defining cars to be agents. Notable examples include Wolshon et al. (2009),Montz et al. (2011) and Montz and Zhang (2013) who applied the ABS package TRANSIMS (Ley, 2009) to hurricane evacuation. Though the households were modeled as agents, the households' decisions and behavior were still treated at the aggregate level. A simplifying assumption was made regarding the evacuation trips and departure time: the departure time distribution was not associated to evacuees' characteristics, rather departure time was assigned based on a zone-level sequential logit model (Montz et al., 2011). A similar approach was used with regard to destination choice and they did not consider pre-evacuation preparation activities explicitly.

ABMS has also been used in pedestrian evacuation (e.g., Lämmel et al. (2010), Liu et al. (2008)). Santos and Aguirre (2004) provided a comprehensive review of the simulation-based evacuation models for pedestrian evacuation in buildings. Though the applications of ABS to hurricane evacuation are limited, ABS has received attention in general transportation planning for daily commutes (e.g., Balmer et al. (2006), Balmer et al. (2009)).

This paper applies the ABMS approach to develop a model system that generates evacuation demand, including pre-evacuation preparation activities in addition to a series of evacuation decisions. This paper makes the following contributions:

- The proposed system is the first comprehensive agent-based evacuation demand model system. It differs from previous TRANSIMS applications in that it relies on stochastic simulation with agents completely characterized by household-level behavioral models and findings. It flexibly represents evacuation decisions by allowing different behavioral model specifications and modeling order;

- It explicitly captures shadow-evacuation demand, leading to a more realistic representation of the evacuate-stay choice;
- It statistically considers the choice of the number of evacuation vehicles through explanatory factors;
- It explicitly models pre-evacuation trips using an activity-based approach. The incorporation of the pre-evacuation trips enhances the accuracy of the demand representation; and
- The output of the model system is evacuation demand represented by activity plans, which can be used for both agent-based traffic simulation tools, such as TRANSIMS and MATSIM, and mesocopic trip-based simulation tools, such as Dynus-T (Chiu et al., 2010).

The survey data used for developing the model components come from three surveys: a post-Hurricane Ivan, hypothetical hurricane in Miami, and post-Hurricane Wilma survey. Details of the surveys can be found in previous papers using the data (e.g., Hurricane Ivan – (Hasan et al., 2013a); Miami survey – (Yin et al., 2013b); Hurricane Wilma – (Noltenius, 2008)).

The remainder of this paper is divided into four sections. Section 2 presents the modeling framework and discusses the specific modules of the model system. Section 3 discusses the implementation of the simulation-based model system. Section 4 presents a sample application to the Miami-Dade area and the last section draws conclusions.

6.2 MODELING FRAMEWORK

6.2.1 Overall Agent-based Modeling Framework

To develop an agent-based representation of the households' travel demand in the evacuation process, it is essential to recognize that this demand is derived from the desire to achieve goals like "going to a safer place" and to participate in various activities such as "shopping for medicine before evacuation." This goal achievement and activity participation are the common threads of the entire evacuation process and are characterized by a series of decisions that are generally made by a household, represented by an agent. An agent's behaviors are described by several related econometric or statistical models.

The simulation framework consists of two related modules: the evacuation decision module, shown in Figure 6.1, and the pre-evacuation activity module, depicted in Figure 6.2 ~ 6.4. The evacuation decision module captures important decisions that a household generally would make during the evacuation process, as identified by Murray-Tuite and Wolshon (2013b). In total, six decisions are captured in the modeling framework. A household would sequentially decide whether to evacuate for the approaching hurricane, choose the accommodation type, and determine the evacuation destination, evacuation mode, and departure time for their ultimate evacuation trip. If a household would use personal vehicles as the evacuation mode, they also need to choose the number of vehicles that would be taken. The pre-evacuation activity module captures households' decisions about engaging in preparation activities such as purchase of food, gas, and supplies. The decision outcomes of the evacuation decision module affect the preparation activities for the upcoming evacuation, which is captured by the pre-evacuation activity module. Specifically, the departure time is translated into the activity planning horizon during which a household would perform various evacuation preparation activities that may require travel. Other decision outcomes may also be used in different components of the pre-evacuation activity module, which will become clear in the following discussion.

The pre-evacuation activity module adopts an activity-based approach, which views the pre-evacuation activity-travel in a tour-stop perspective. Activity-based models are widely used for regular planning purposes (Pendyala and Ye, 2005), such as the modeling system developed by Bhat et al. (2000; 2001; 2002). However, evacuation activity travel behavior is different from that under normal conditions.

Regular planning activity travel models generally focus on a 24-hour planning horizon while evacuation preparation activities usually span days and involve activities that allow evacuees to effectively plan for evacuation. During a day or two prior to departure a household may perform the activities that are performed in a week under regular conditions due to the evacuation needs. The pre-evacuation activity module consists of three sub-modules: an activity generation sub-module, passenger household assignment sub-module, and an activity scheduling sub-module. The activity generation sub-module captures households' decisions about whether to engage in any out-of-home preparation activities. If a household participates in such activities, it simulates households' decisions of the number of tours and the activities that would be pursued in these tours, such as fueling automobiles and picking up friends. The decision outcomes of the activity generation sub-module are then used in the passenger household assignment sub-module. Since some households rely upon their friends or relatives to reach their evacuation destinations, this sub-module matches these passenger households with households that have picking-up responsibilities generated by the activity generation sub-module. The third module, the activity scheduling sub-module, then assigns specific action days, times and locations to these activities via simulation.

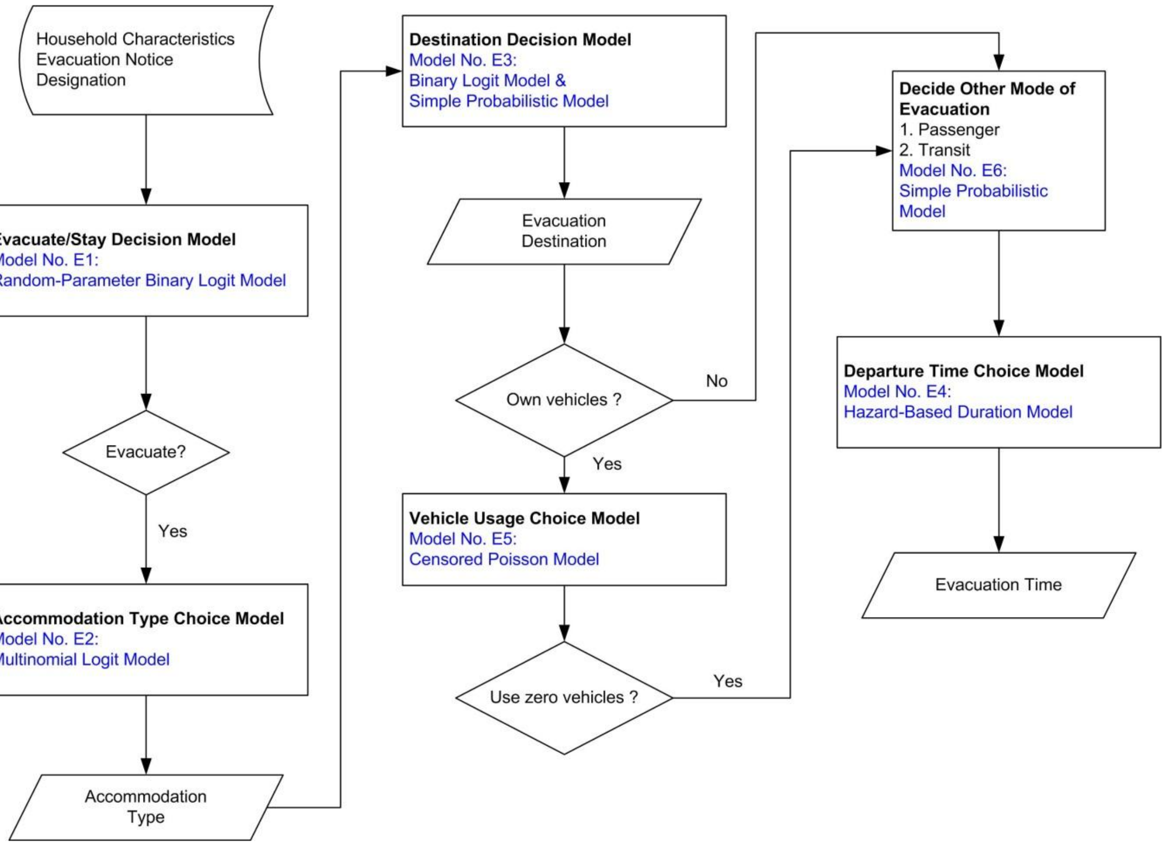

Figure 6.1 The Structure of the Evacuation Decision Module

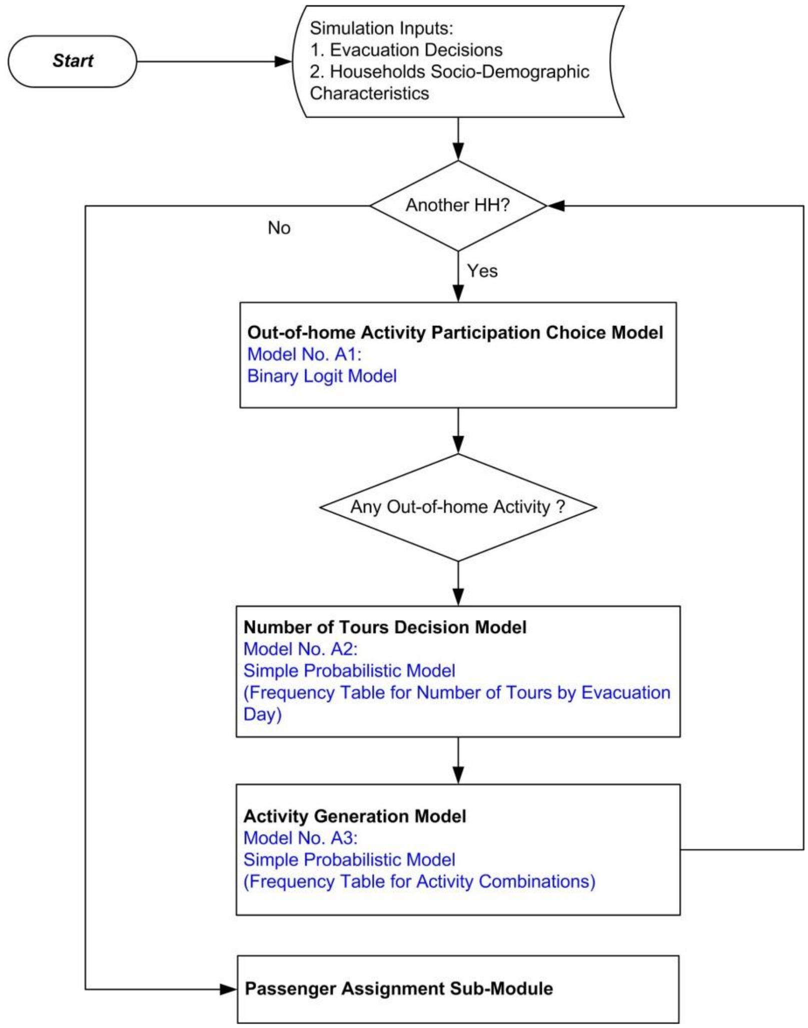

Figure 6.2 The Structure of the Activity Generation Sub-Module

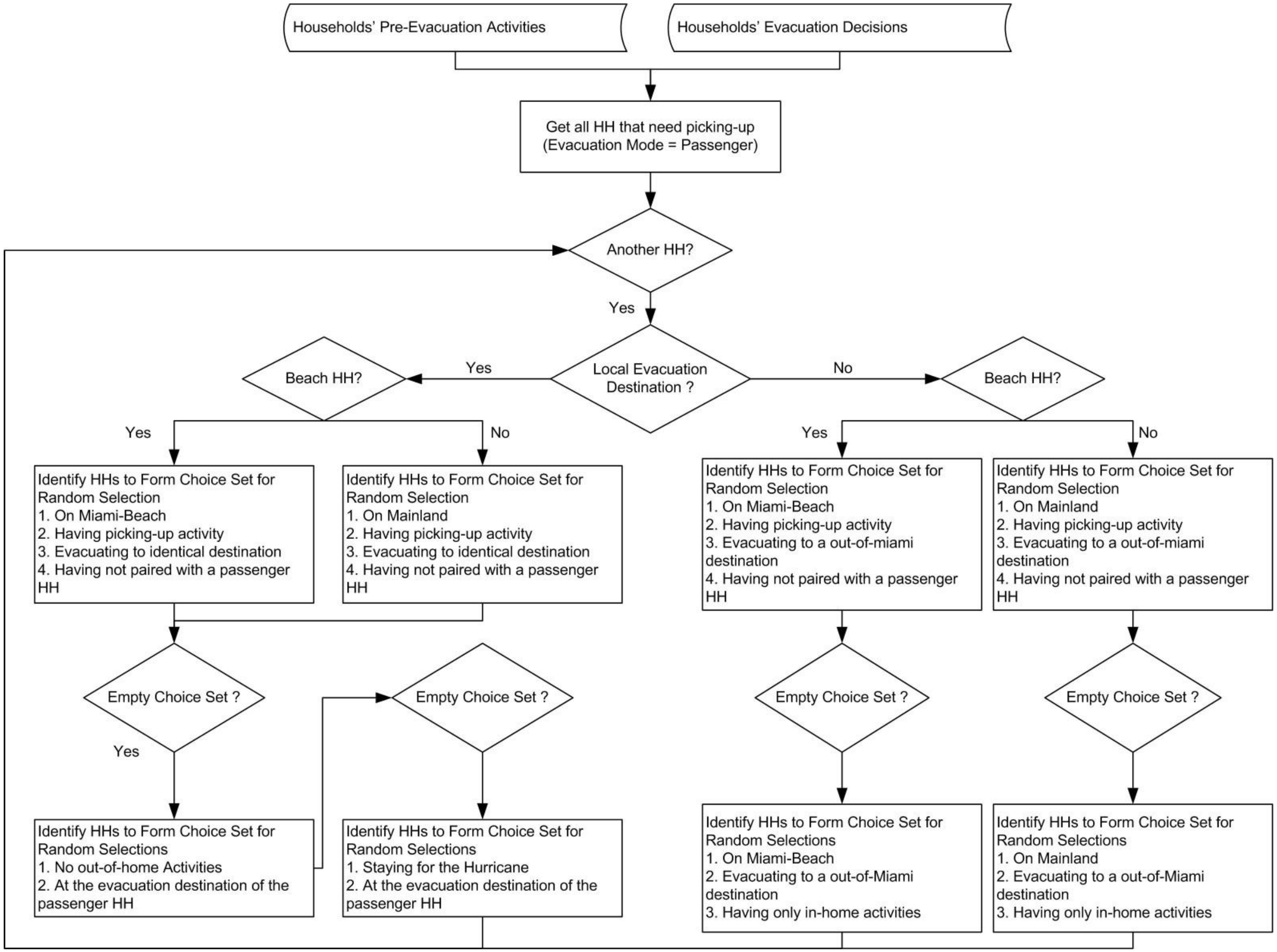

Figure 6.3 The Structure of the Passenger Household Assignment Sub-Module

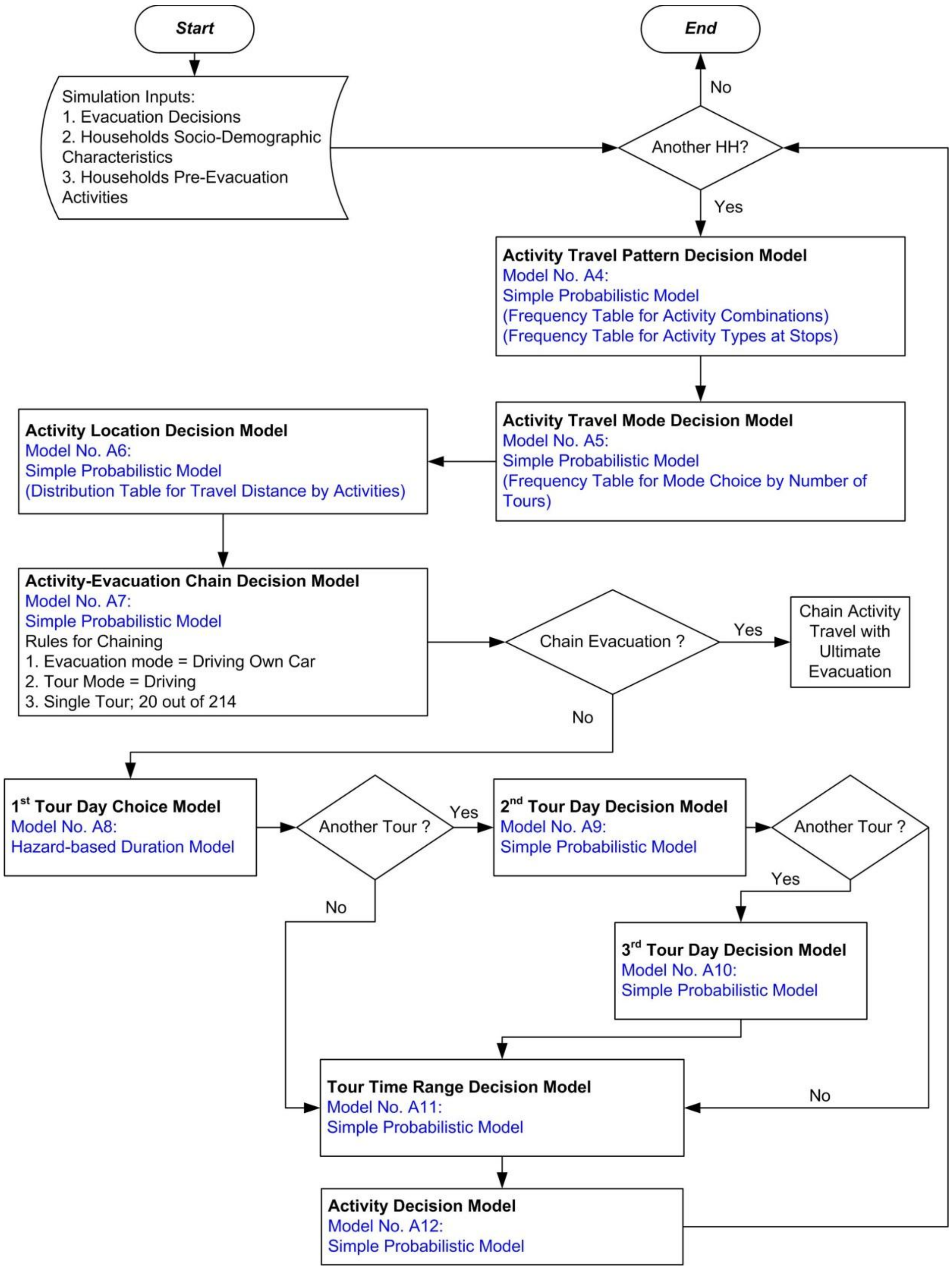

Figure 6.4 The Structure of the Activity Scheduling Sub-Module

6.2.2 Evacuation Decision Module

The evacuation decision module starts with the decision of whether to evacuate for the approaching hurricane. This decision has been the subject of many behavioral and engineering studies (Yin et al.

(2012a); Murray-Tuite and Wolshon, 2013). To capture shadow evacuation, defined as people evacuating from outside the official evacuation zone (Zeigler et al., 1981), a random-parameter logit model is estimated using the post-Hurricane Ivan survey to determine agents' behavior for the evacuate/stay decision. The households' distances to the coast are calculated using their home coordinates and then normalized by the maximum distance to derive the relative distance to the coast, denoted by "[reldist]". Normally distributed random coefficients are associated with three variables: "[haswkdut]", "[noevacnt]," and "[nonmandn]." The random coefficients of the latter two variables capture households' different perceived risk of the approaching hurricane, which contributes to their evacuate/stay decisions. In addition, a statistically significant heterogeneous mean is found for the random coefficient of "[noevacnt]," which associates the perceived risk with the distance to coast. The estimation results are shown in Table 6.1.

Table 6.1 The Estimation Results of the Evacuate/Stay Choice Model

Variable	Description	Evacuate/Stay Model
Nonrandom parameters		*Coefficient (Standard Error)*
[winprote][a]	The HH has window protection	-0.309*** (0.077)
[bizown][a]	A HH owns business	-0.198* (0.104)
[childu17]	Number of Children under 17	0.105*** (0.034)
[mobile][a]	HH lives a mobile home	1.078*** (0.171)
[inco80k][a]	HH's income is over 80,000 USD	0.202** (0.088)
[lthighsc][a]	HH's education level is less than high school	-0.396** (0.183)
[pgrad][a]	HH's education level is post-graduate	0.355*** (0.106)
[pet][a]	HH owns pet(s)	-0.201** (0.081)
[reldist]	HH's relative distance to coast	-0.530** (0.231)
[statefl][a]	HH lives in Florida	-0.805*** (0.100)
[Constant]		1.470*** (0.164)
Means for Random Parameters		
[haswkdut][a]	HH's members had work duty before evacuation	-0.197** (0.083)
[noevacnt][a]	HH did not receive evacuation notice	-1.428*** (0.163)
[nonmandn][a]	HH received non-mandatory evacuation notice	-0.667*** (0.113)
Variances for Random Parameters		
[haswkdut]		1.231*** (0.112)
[noevacnt]		0.628*** (0.080)
[nonmandn]		0.618*** (0.102)
Heterogeneity in the mean of [noevacnt]		
[stateFL]		1.020*** (0.210)
[reldist]		-0.976** (0.425)

a. This variable is an indicator variable which takes value "1" if the statement is true.
Number of Observations: 2679, Log likelihood = -1183.348, Outcome = 1 represents a household chose to evacuate. $\chi2$= 29.56 and P-value for chi-square test = 0.003.
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The model is statistically significant as shown by the likelihood chi-square test whose null hypothesis that all coefficients are zero is rejected at the 0.001 significance level. The fixed coefficients generally show signs similar to existing studies (e.g., Yin et al. (2012a)). For instance, households with higher income and education attainment are more likely to evacuate. Households that did not receive mandatory evacuation notices are less likely to evacuate. The household-level heterogeneity of the random coefficient for the variable "[noevacnt]" is manifested via the inclusion of the relative distance to coast variable. This allows households who do not receive any evacuation notice to assume different distributions for the random parameter depending on their distance to coast. Specifically, the sign of the relative distance to coast is -0.976 for the mean of the random parameter of variable “[noevacnt]”, suggesting that the likelihood of evacuation for households that did not receive any evacuation notice decreases as their distance to coast increase on average. A later application to the Miami-Dade area demonstrates this effect.

If a household decides to evacuate, then they need accommodations, which can be a shelter, a friend’s or family members’ home, or a hotel, among other choices. Accommodation type choice is modeled by a multinomial logit model with three alternatives: a friend’s/relative’s home, shelter, and hotel. Since the later application is for the Miami-Dade area, the model is estimated using the corresponding behavioral intention survey. The estimation results are shown in Table 6.2.

Table 6.2 The Estimation Results of the Accommodation Type Choice Model, Local/Out-of-Miami Destination Choice Model, Departure Time Choice Model and Out-of-Home Activity Participation Choice Model

Variable	Description	Accommodation Type Choice Model		Local/out-of-Miami Destination Choice Model	Departure Time Choice Model	Out-of-Home Activity Participation Choice Model
		Hotel[b]	Public Shelter[b]			
[incu10k][a]	HH's income is less than 10,000 USD	-1.144**(0.497)				
[inc1020k][a]	HH's income is between 10,000 to 20,000 USD		1.219***(0.441)	0.717*(0.400)		
[hispn][a]	HH has Hispanic members	-0.759***(0.273)		0.614**(0.236)		
[rent][a]	HH rents the current home.		1.341***(0.400)			
[friend][a]	A HH evacuates a friend/relative's home			1.425*** (0.270)	-0.319***(0.118)	
[shelter][a]	A HH evacuates a public shelter				-0.358*(0.208)	
[colgrad][a]	HH's education level is college graduate					0.325*(0.198)
[pgrad][a]	HH's education level is post-graduate			-0.726** (0.269)		
[hhsize]						0.136*(0.0732)
[chldu12]	Number of Children under 12			-0.501**(0.232)		
[over64]	Number of HH members over 64 years old				0.143**(0.067)	-0.273**(0.126)
[sfh][a]	HH lives in a single family house			-0.812**(0.290)		
[owncar][a]	HH uses their own vehicles to evacuate				0.221*(0.120)	0.919***(0.231)
[constant]		-0.647***(0.139)	-2.990*** (0.330)	-1.413**(0.273)		-0.893***(0.268)
Number of Observations		414		414	414	462
Log-Likelihood		-315.85		-229.2247	-2094.355	-301.429
χ2 statistic		42.88		57.99	16.44	37.47
P-value for chi-square test		<0.001		<0.001	0.002	<0.001
a. This variable is an indicator variable which takes value "1" if the statement is true. b. Friend/Relative's home is the reference category. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

The model is statistically significant at the 0.001 significance level. The coefficients indicate that households with income less than 10,000 USD are less likely to go to a hotel compared to a friend/relative's home. Households living in rented properties are more likely to go to a public shelter than to a friend/relative's home.

After a household selects their accommodation type, they need to choose their evacuation destination. This choice is captured by a two-step model using the Miami survey data. A household first decides whether to evacuate to a local destination or one outside the Miami-Dade area. This choice is captured by a binary logit model. If the household decides to go to a local destination, then a specific city is assigned as their evacuation destination region based on a city-by-city frequency count from the Miami survey. If they choose a non-local destination, they are assigned to one of the super destinations representing the out-of-Miami destinations. The estimation results of the local/out-of-Miami destination choice model are shown in Table 6.2. The model is statistically significant at the 0.001 significance level. The coefficients suggest that households with income between 10,000 and 20,000 USD are more likely to go to a local destination. Households choosing friend/relative's homes as accommodations are more likely to go to a local destination. On the other hand, households living in single family houses and those with post-graduate degrees are less likely to choose a local destination and the likelihood of staying locally decreases if a household has more children under 12 years old.

Following the evacuation destination choice, the household chooses their evacuation mode. Many studies found that personal vehicles remain the dominant evacuation mode (e.g., Wu et al. (2012)). If a household owns vehicles, a vehicle usage choice model estimates the number of vehicles used. The model explicitly considers the factors contributing to households' choice of the number of vehicles used and the constraint imposed by the number of vehicles owned by the household. The right-censored Poisson model developed by Yin et al. (2013a) using the Hurricane Ivan survey data is used here and the estimation results are reproduced in Table 6.3. The variable "[dur]" in the vehicle usage choice model is derived from a simulation using the observed sample departure curve. Later, the departure time choice model will assign the ultimate departure time.

Table 6.3 Estimation Results of the Vehicle Usage Choice Model and Action Day Choice Model for the First Tour

Variable	Description	Vehicle Usage Choice Model	Action Day Choice Model for the First Tour
[numveh]	The number of vehicles owned by the household	Censoring Variable	
[logdist]	The log of the travel distance to the evacuation destination	-0.0618***(0.0182)	
[dur]b	The stay duration in hours until evacuation	-0.00367**(0.00143)	-0.036*** (0.004)
[num18to80]	The number of people between 18 and 80 years old	0.148***(0.0309)	
[hurrexp][a]	The household had hurricane experience before Ivan	0.159***(0.0554)	
[pgrad][a]		-0.129**(0.0559)	
[pet][a]	The household had pets	0.144***(0.0477)	
[mobile][a]	The household lived in a mobile home	0.264***(0.0961)	
[stateFL][a]	The household lived in Florida	-0.119**(0.0511)	
[day2]	Dummy Variable for Day 2 (Sun.)		0.269 (0.257)
[day3]	Dummy Variable for Day 3 (Mon.)		1.480*** (0.279)
[day4]	Dummy Variable for Day 4 (Tue.)		2.725*** (0.359)
[day5]c	Dummy Variable for Day 5 (Wed.)		
[numtours]	Number of Tours to be performed		1.549*** (0.363)
[med]a	One Stop in Tour 1 is purchase of medicine		0.482* (0.285)
[pickup]a	One Stop in Tour 1 is picking-up people		-1.308** (0.514)
Constant		0.515***(0.156)	0.0859 (0.498)
Number of Observations		767	579
Log-Likelihood		-708.685	-309.377

a. This variable is an indicator variable which takes value “1” if the statement is true.
b. For the action day choice model, this variable represents the length of the planning horizon in hours, calculated as the time duration from Saturday midnight to the selected evacuation departure time.
c. The dummy variable for Day 5 predicts the occurrence of tour 1 perfectly and hence is removed from the regression model (13 observations).
Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

If a household does not own vehicles, they either rely on public transit or their friends’ evacuation vehicles. This assignment is based on a frequency table derived from the Miami survey.

The final decision is the departure time, which is captured by a semi-parametric hazard-based duration model, or the well-known Cox model (Greene, 2012). Since the baseline hazard of the Cox model is a non-parametric specification, this offers great flexibility for capturing the shape of the departure curve, which generally is a multiple S-curve due to concentrated departures in the morning and afternoon. The profile of the departure curve will become clear in the application section. The model, shown in Table 6.2, is estimated using the Miami survey data.

The model is statistically significant at the 0.05 significance level. The estimated coefficients suggest that households evacuating to a shelter or a friend's or relative's home are more likely to evacuate late compared to those evacuating a hotel. Households using their own vehicles are more likely to evacuate earlier compared to those relying upon transit or those needing picking-up. More household members over 64 years old contribute to increased likelihood of early departure.

This concludes the evacuation decision module. The specific sequence of decisions is imposed here based on the available survey data. The simulation framework is not constrained by the model specification and can take other behaviorally justifiable decision orders.

6.2.3 Pre-Evacuation Activity Module

The pre-evacuation activity module is developed using the Miami survey in which households were asked for details regarding the activities they would engage in before they embark on the ultimate evacuation trip, including the activity's purpose, location, and action time (i.e., day and time range); travel mode; and whether the activity is chained with the ultimate trip. Through open ended questions, the survey requested the most important, travel-involving activities that respondents would participate in prior to departing for their ultimate evacuation destinations though in-home activities were also reported. These data have been analyzed and the findings are reported in Yin et al. (2013b). Here the general logic, as depicted in Figure 6.2, Figure 6.3 and Figure 6.4 for activity generation and scheduling is described.

The planning horizon of a household is the time duration from the start of the planning horizon until their evacuation departure. The pre-evacuation activity module adopts the generation-scheduling paradigm used in some regular planning applications such as Bhat et al. (2004). The activity generation sub-module starts with the model that captures households' decision as to whether to engage in any out-of-home activities. This model is necessary since many respondents reported only in-home activities despite the request of reporting activities involving travel. The binary logit model developed in Yin et al. (2013b), shown in Table 6.2, suggests that larger households and those with college graduates are more likely to engage in activities that require travel; households choosing to drive their own vehicles are more likely to participate in out-of-home activities; and the number of people older than 64 has a negative impact upon engaging in out-of-home activities.

If a household performs out-of-home activities, they then decide the number of tours they would make. Since the number of households making two or more tours is limited, the number of tours is not modeled econometrically. In addition, to ensure that the simulated number of tours can be completed within the household's planning horizon, a simple probabilistic model based on the frequency distribution between number of tours and evacuation day is used. This approach reflects the observation that households evacuating late are more likely to make multiple tours. After the number of tours is determined, the activity generation sub-module (Figure 6.2) assigns the specific activities pursued in these tours based on the frequency distribution of activity combination by number of tours. Specifically, the number of tours is used as the input and the activity combination is simulated based on the frequency distribution corresponding to that particular number of tours. For example, if a household would make two tours, the possible activity combinations are those with non-zero percentages. For example, two possible activity combinations for making two tours include purchase of food, gasoline, and medicine and the other involves just gasoline and withdrawal of cash.

After all households have been assigned activity combinations, the passenger assignment sub-module pairs the households whose evacuation mode is passenger with those assigned picking-up activities. The sub-module first identifies all the passenger households and treats each one according to their evacuation destination. Since the Miami survey data suggested that the households living on Miami Beach would only pick up others living on Miami Beach, the sub-module also include the home location as one decision criterion. For instance, if a passenger household lives on Miami Beach, the sub-module initially searches for those on the island who evacuate to an identical evacuation destination and are assigned picking-up activities. If such households exist, one household is randomly selected as the picking-up household for this passenger household. If no household matches these criteria, the sub-module then searches for those on the island who evacuate to an identical evacuation destination and have only in-home activities. If the choice set formed by these households is not empty, a random selection is conducted. Otherwise, the passenger household is paired with a household who does not evacuate for the hurricane and resides at the passenger household's evacuation destination. Similar steps are taken for households living off Miami Beach and going to an out-of-Miami destination. After all the passenger households are matched with picking-up households, the activity combinations are updated for those households that were not assigned picking-up activities initially. The updated activity combination for each household is the input for the subsequent scheduling.

The activity scheduling sub-module (Figure 6.4) first assigns the activity travel pattern, including the number of stops for each tour and the specific activities pursued at each stop. The input to this model is the number of tours and activity combinations selected in the previous sub-modules. The distinct activity patterns are identified based on the survey responses. For instance, if a household's activity combination is withdrawal of cash and purchase of food for a single tour, three distinct activity travel patterns exist in the survey. The tour-maker from the household might first make a stop to withdraw cash and then go to buy food or make the stops in the opposite sequence or make only one stop for cash and food together. The counts for these distinct travel patterns are used as a simple probabilistic model for simulation purposes.

After the activity travel pattern has been decided, the travel mode for each tour is needed. The tour mode choice is based on the frequency table using number of tours and activity combinations as decision factors. If purchase of gas is among the activities pursued in a tour, the mode is driving. The survey also suggested that the mode for a picking-up tour is driving.

Following mode choice, an activity location is assigned for each stop based on the activity type pursued at that stop number. About half of the respondents provided addresses and location information for their activities and these locations were geocoded using ArcGIS. The distances between stops and home by activity type is used to simulate the travel distance between stops. The stop locations are fairly close to respondents' homes, with less than 2-miles average distance. The distance between the first and second stops for multi-stop tours has a mean of 0.90 miles and a standard deviation of 1.81 miles. The locations that are within half a mile of the simulated travel distance compose the choice set from which a random selection is made. The location of a picking-up activity is the passenger household's home.

Some households may chain their tours with the ultimate evacuation trips. This decision is captured by the activity-evacuation chain decision model. The rules are developed from the observations involving the activity-evacuation chaining behavior of the Miami survey. Approximately 10% of the households who would make a single tour in their own vehicles would chain the activities with the ultimate evacuation trip. If the activity travel is chained with the ultimate evacuation, the action time is the evacuation departure time and no additional scheduling is necessary. If the activity travel is not chained with evacuation, the action day of the first tour is decided by the first-tour day choice model taking the form of a hazard-based discrete duration model. The action day for the first tour is statistically significantly related to the activity type and the households' selected evacuation times. For a complete discussion of the model, see Yin et al. (2013b). If a household makes more than one tour, 75% of the households (16 out of 21) perform the second tour on the same day of or the day following the day of their first tour. The third tour is uniformly one day after the second tour. The tour time range is assigned according to the frequency distribution found in Yin et al. (2013b). After the tour time range is determined, a specific time is simulated using a uniform distribution constructed based on the time range. For example, if a household makes a tour in the morning, the action time is randomly selected from 8 am to 12 pm.

The last piece of the activity scheduling sub-module is the activity duration decision model, which takes the form of a truncated normal distribution. The duration for shopping activities is assumed to follow N(25, 15) with a minimum of 10 minutes and a maximum of 60 minutes. The distribution for the duration of picking-up activity is assumed to follow N(57, 76) with a minimum of 45 minutes and a maximum of 120 minutes, based on Noltenius (2008).

These three sub-modules form the pre-evacuation activity module. The outputs of this module are the activity plans that describe the activity travel prior to evacuation departure and the ultimate evacuation trips. A sample activity plan is: a person makes a two-stop tour on Monday at 2:23 pm by driving. The first stop is purchase of food and the second stop is fuelling the vehicle. The household evacuates on 8:20am Tuesday to an out-of-Miami location by driving.

6.3 SIMULATION IMPLEMENTATION

The implementation of the agent-based travel demand model system includes two components: the simulation algorithms for generating disaggregate predictions and the software architecture to coordinate the modules.

6.3.1 Simulation Algorithm for Generating Disaggregate Predictions

The modeling system's primary goal is to produce simulated activity-travel plans by stepping through each module outlined in the previous sections to predict the corresponding choice outcome. There are two aspects to the prediction process: the generation of disaggregate predictions for each individual component model and the integration of the decision outcomes into one final activity-travel plan.

One approach for predicting individual decision outcomes involves selecting the alternative with the highest probability for each of the model components with discrete outcomes and using expected value predicted by the model for a continuous choice variable. However, this methodology introduces systematic bias in the outcome of each modeling step (Bhat and Misra, 2001) and contradicts the probabilistic nature of the decision model (Train (2002)). Consequently, the cumulative prediction errors for a large model system such as the one proposed can be quite significant.

An alternative approach involves a full decision tree in which the probabilities of all the alternatives are carried over to the root node (Bhat et al., 2004). The chosen set of alternatives can be subsequently determined by extracting the path with the highest path probability in the decision tree (Bhat et al., 2004). But, this approach can be computationally intensive for many decision outcomes. More importantly, decision trees cannot handle models with continuous choice outcomes.

The general simulation mechanism adopted here resembles the one proposed by Bhat et al. (2004) which eliminates the bias of the first approach while avoiding the computational complexity of the latter approach. In the case of discrete choices, the chosen alternative is determined by identifying the distribution of the alternatives whose probabilities are predicted by the model component based on relevant covariate values derived from households' characteristics and previous decisions. Subsequently, a random draw is taken from the uniform distribution, and depending on the magnitude of this number, the corresponding alternative is declared as the chosen alternative. For the continuous choice instances, the choice is determined by a random draw from the probabilistic distribution of the choice variable defined by the associated econometric or statistical model. Thus, the chosen continuous outcome is not identical for all observationally similar decision makers.

The econometric specifications for the model components include regular and random-parameter binary logit models, a multinomial logit model, continuous and discrete hazard-based duration models, a right-censored Poisson model, and simple probabilistic models. The algorithms for identifying the probability distribution of the choice outcomes for the commonly-used models, namely the regular binary logit models, multinomial logit model, and simple probabilistic models are established in Bhat et al. (2001) and are used here. The method for simulating probabilities of choice alternatives for the random-parameter binary logit model is outlined in Train (2002) and Greene (2012). The algorithm for the right-censored Poisson model is described in Yin et al. (2013a). The algorithm for the continuous hazard-based duration model can be found in Bender et al. (2005) and Austin (2012) and an identical method can be used for its discrete counterpart once the cumulative hazard function is computed using the method developed by Rabe-Hesketh and Skrondal (2012).

6.3.2 Software Architecture

The model system was developed using the object-oriented (OO) paradigm. Through the process of OO analysis, a number of major entities involved in the simulation of activity-travel plans were identified. The system architecture includes the input/output database, the data entities such as household, person, tour and stops, and modeling modules like the econometric models. A GIS engine, namely, Spatialite, is also embedded to provide the geospatial query capability required for the activity stop location decision model. The program is written in C++. On average, it takes about 0.3 seconds to generate the activity plan for one household.

6.4 APPLICATION TO THE MIAMI-DADE AREA

The model system is applied to the Miami-Dade area for a hypothetical category-4 hurricane, which would make landfall on Wednesday. The evacuation warning would be issued at 8:00 AM Saturday. The overall planning period is from 12:00 AM Saturday to 12:00 PM Thursday. The reason for including the period before the evacuation notice and after landfall is that some survey respondents indicated that they would evacuate in these two periods. A synthetic population generator provided in the TRANSIMS package (Ley, 2009) was used to translate the aggregate demographics to a disaggregate population of households and individuals within the household for the Miami-Dade region. Then the evacuation zones are identified based on the data provided by the Miami-Dade emergency management agency. Using these inputs, the program generates the travel demand.

The comparison between the distributions of the evacuation decisions for the simulation and the survey response is documented in Table 6.4.

Table 6.4 Comparison of Distributions of Evacuation Decisions

Decision	**Simulation**	**Survey**
Evacuate/Stay	Evacuate: 88.98% (In Evacuation Zone), Evacuate: 22.85% (Shadow Evacuation)	Evacuate: 85.71%
Accommodation Type	Friend: 65.82%, Hotel: 24.59%, Shelter: 9.59%	Friend: 67.15%, Hotel: 24.40%, Shelter: 8.45%
Evacuation mode	Car: 90.61%, Passenger: 5.89%, Transit: 3.49%	Car: 73.3%, Passenger: 9.9%, Transit: 16.8%
Local Destination	Local: 36.45%	Local: 41.58%
Vehicle Usage[a]	1 Vehicles: 71.78%, 2 Vehicles: 21.51%, 3 Vehicles: 3.82% 4 Vehicles: 1.40%, 5 Vehicles: 1.47%	1 Vehicles: 66.71%, 2 Vehicles: 25.91%, 3 Vehicles: 5.16%, 4 Vehicles: 0.59%, 5 Vehicles: 0.35%
(a) The vehicle usage was not reported in the Miami survey. Hence the simulation results are compared to the Hurricane Ivan survey.		

The simulated proportion of the evacuation households is 88.98% in the evacuation zone, which is slightly higher than the reported 85.71% of the Miami survey. The current program assumes full penetration of the evacuation warning while some survey respondents suggested that they do not know whether they are in an evacuation zone. The shadow evacuation percentage is 22.85%, which is close to the average 26% reported by Sorensen and Vogt (2006). The geographical distribution of the evacuation population is depicted in Figure 6.5. The heat map in Figure 6.5 suggests that the major proportion of the shadow evacuation population lies within 1.86 to 3.11 miles of the mainland coastline.

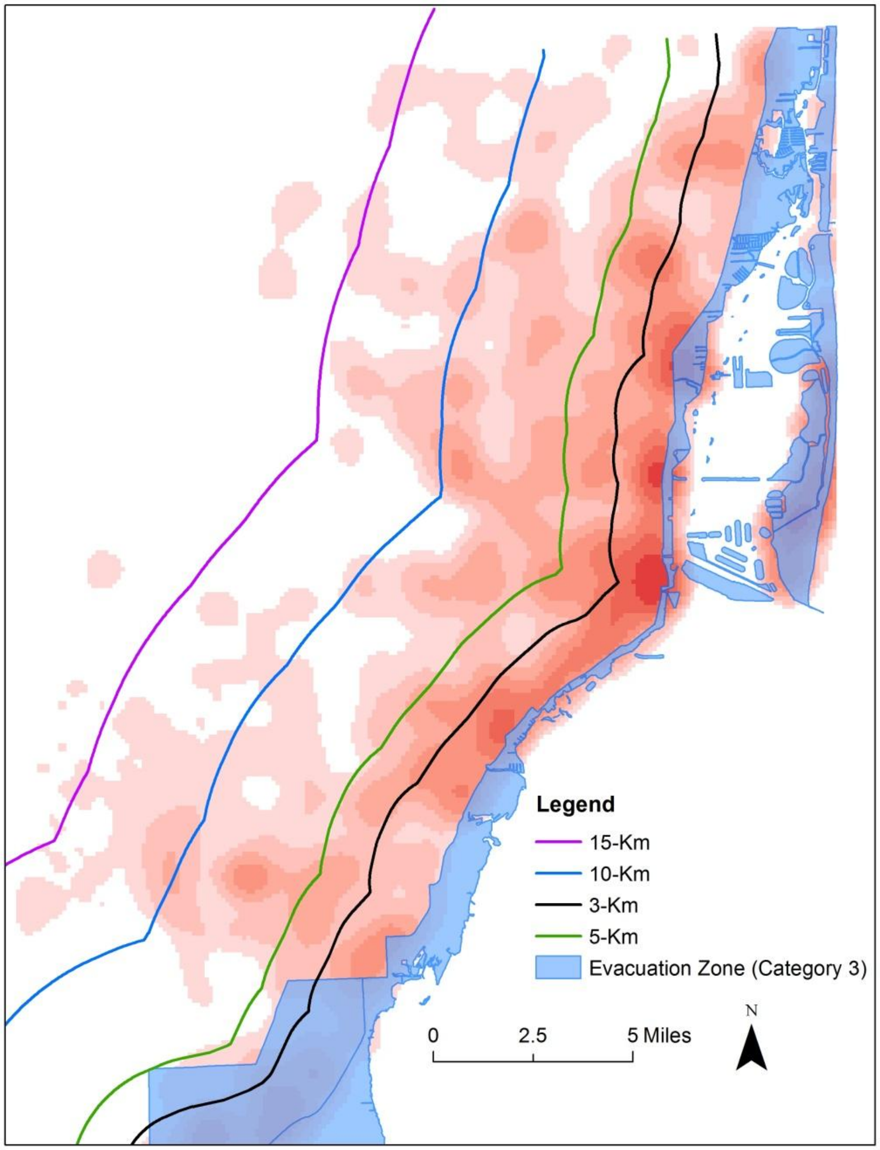

Figure 6.5 The Geographical Distribution of the Evacuation Population (Darker red indicates more evacuees)

The simulated distribution of the accommodation type choice outcomes is very similar to that reported in the Miami survey, evidenced by an absolute error less than 1%. The proportion of households that choose their own vehicles as the evacuation mode is 90.61%, which is higher than that reported in the Miami survey. But a similar percentage was reported in previous studies (Lindell et al., 2011; Wu et al., 2012). The Miami survey reported approximately 15% of evacuees using transit, which is a lot higher than what existing studies (Lindell et al., 2011; Wu et al., 2012) reported. The Hurricane Ivan survey results indicated that all transit evacuees did not own vehicles. Unfortunately, the Miami survey did not ask whether a household owns any vehicles. Therefore, it is possible that the evacuees without vehicles are over-sampled which contributes to the higher percentage of transit evaucees. In addition, the Miami survey did not include respondents from the mainland, which may contribute to this difference. This may also be the reason for a slight difference in the distribution of destination choice outcomes and the vehicle usage choice.

The comparison between the simulated departure time curve and the reported one is shown in Figure 6.6.

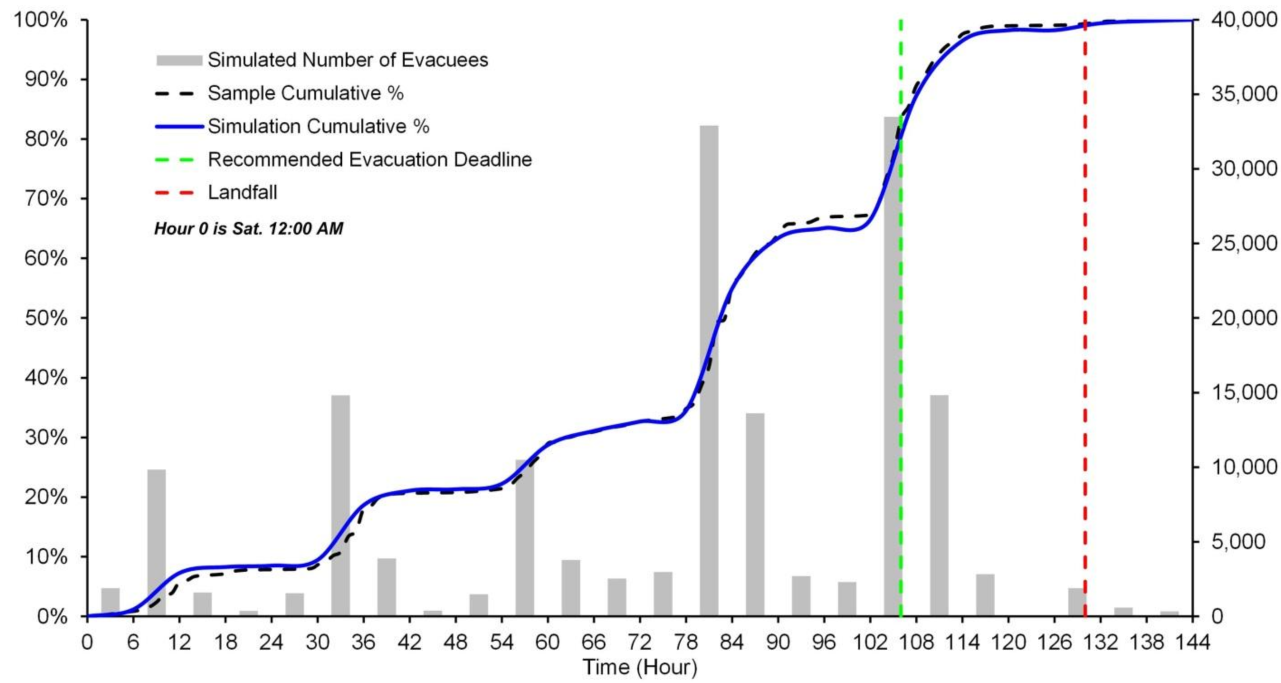

Figure 6.6 The Comparison between Simulated and Reported Departure Time Curve

The simulated departure curve closely aligns with the reported curve. More importantly, the multiple S-curve, due to concentrated departures in morning and afternoon, is well produced due to the non-parametric nature of the baseline hazard of the departure time choice model. This is also the reason why a parametric duration model was not used due to its inability to capture the concentrated departures.

The activity plans are assigned to actual routes based on the all-or-nothing rule and posted speed limits using the Router utility in the TRANSIMS package (Ley, 2009). The 24-hour cumulative vehicle count on the fourth day, on which the highest evacuation departures occur, is shown in Figure 6.7. Clearly, the major roads such as interstate 75 and 95, Palmetto Expressway, Florida Turnpike, S. Dixie Highway, and the bridges connecting Miami Beach and the mainland carry considerable amounts of traffic. The authors and their colleagues are currently simulating the generated demand using an agent-based traffic simulation tool for the Miami-Dade region.

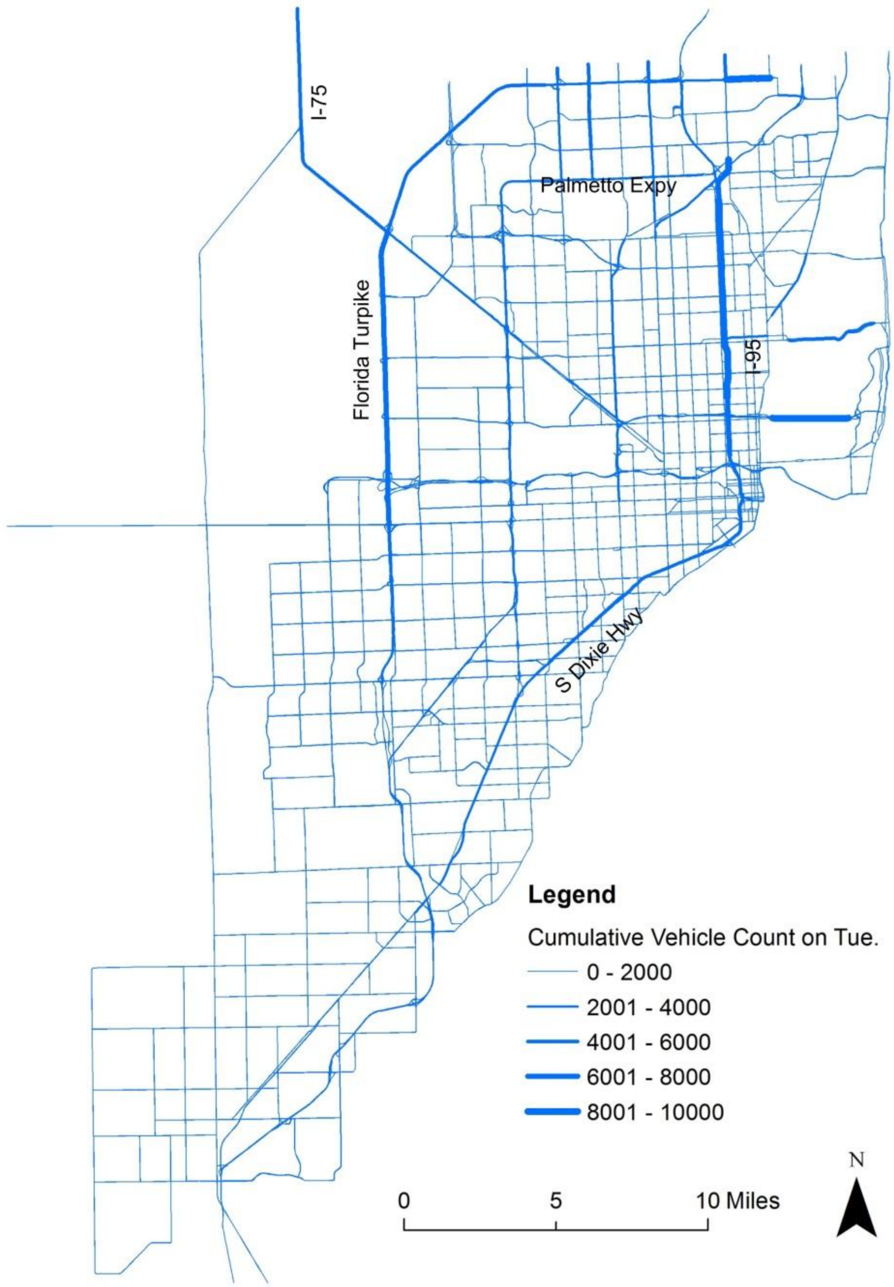

Figure 6.7 24-Hour Cumulative Vehicle Count for Tuesday under All-or-Nothing Assignment

6.5 CONCLUSIONS AND FUTURE DIRECTIONS

This paper presents an agent-based travel demand model system for hurricane evacuation simulation, which is capable of generating comprehensive activity-travel plans for households. The system implements econometric and statistical models that represent travel and decision-making behavior throughout the evacuation process, and is flexible enough to adopt alternative behavioral models. It generates the predicted activity-travel patterns for all households in the simulation sample. Traffic assignment methods can be applied to determine traffic patterns on the network. The system considers six typical evacuation decisions, namely evacuate/stay, accommodation type, evacuation destination, mode, vehicle usage, and departure time in addition to the pre-evacuation activity generation and scheduling. The model system possesses the following major strengths:

- Unlike most previous models, this system explicitly captures the shadow evacuation population and produces the percentage of shadow evacuation demand close to that reported in existing studies.
- The model system reproduces the desired temporal pattern for the evacuation departures and links the departure time choice with household characteristics.
- The model system is the first to explicitly capture the pre-evacuation preparation activities via the generation-scheduling paradigm.
- The simulation mechanism of the model system recognizes the taste variation and ensures that the chosen outcome is not identical for all observationally similar decision makers, which is a major distinction from the simulation models using a deterministic decision-maker matching algorithm such as the demand module in TRANSIMS for regular planning (Ley, 2009).

A demonstration predicts activity-travel patterns using model parameters estimated for the Miami-Dade area. The simulation results indicate the model system produced the distribution of choice pattern that is consistent with sample observations and existing literature. The model system is also able to identify the proportion of the shadow evacuation population and their geographical extent. Specifically, approximately 23% of the population outside the designated evacuation zone would evacuate, which echoes the findings in previous studies. The shadow evacuation demand is mainly located within 5 km (3.11 miles) from the coastline. A static traffic assignment for the day with highest evacuation demand shows that the major roads would carry significant amounts of evacuating traffic, as expected. The output demand of the system works with agent-based traffic simulation tools as evidenced by the ongoing effort of applying dynamic traffic assignment to determine travel demand patterns on the Miami-Dade network.

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CHAPTER 7 CONCLUSIONS, ENGINEERING SIGNIFICANCE, LIMITATIONS AND FUTURE DIRECTIONS

This chapter is organized into three sections. The first section draws conclusions about the main findings of the dissertation. The second section discusses the engineering significance of the dissertation's contributions and a few limitations. The third section identifies potential directions for future research.

7.1 CONCLUSIONS

This dissertation investigates the evacuees' behavior under hurricane evacuation conditions and develops an agent-based travel demand model system for hurricane evacuation simulation using these behavioral findings. The dissertation econometrically models several important evacuation decisions including evacuate-stay, accommodation type choice, evacuation destination choice, evacuation mode choice, departure time choice, and vehicle usage choice. In addition, it explicitly considers the pre-evacuation preparation activities using an activity-based approach. The models are then integrated into a two-module agent-based travel demand model system.

The dissertation first presents the evacuate-stay choice model using the random-coefficient binary logit specification. The estimation results suggest that the households that have window protection are less likely to evacuate. Similarly, households that own businesses are less likely to evacuate. In addition, households in mobile residences are more likely to evacuate. Some socio-demographic factors also contribute to the decision. For instance, households with higher income and education attainment are more likely to evacuate. The number of children under 17 also shows a positive impact upon the evacuation. Households that have pets are less likely to evacuate. The model uses heterogeneous mean of the random parameter across households to capture shadow evacuation. It is found that the likelihood of evacuation for households that do not receive any evacuation notice decreases as their distance to coast increases on average. Recognizing the observation that the perceived risk is sensitive to households' distance to the coast and it decreases as the distance to the coast increases, the distance sensitivity factor, or DSF, is introduced to construct different scenarios of the geographical extent of shadow evacuation. The study provides implications for both emergency management and evacuation modeling. The emergency management agencies should understand that the geographical extent of shadow evacuation may be extensive and thus should be prepared for the additional demand generated from the low-risk areas and relevant traffic management strategies and plans should be designed.

The dissertation then presents statistical analysis of the vehicle usage choice. Two variants of the regular Poisson regression model are explored for the vehicle usage choice based on a post-storm survey for Hurricane Ivan: the Poisson model with exposure and right-censored Poisson regression. The two models explicitly consider the fact that the number of vehicles used for evacuation cannot exceed the number of vehicles owned by the household, which the ordered-response models fail to accommodate. Between the two models, the right-censored Poisson model is preferred due to its capability of assigning zero probabilities to the number of vehicle used larger than the number of vehicles owned, its better measures of fit and superior predictive power. Using the right-censored Poisson model, it is found that

1. Households that travel longer distances are more likely to use fewer vehicles;
2. Households who evacuate late are statistically more likely to use fewer vehicles;
3. Households with previous hurricane experience are more likely to use a greater number of vehicles;
4. The number of household members between 18 and 80 years old is positively related to the number of vehicles taken on the evacuation;
5. Household income has no statistically significant impact upon the number of household evacuation vehicles chosen (recall that the model specification accounts for the number of vehicles owned by the household);
6. Pet-owning households are statistically more likely to evacuate with more vehicles than households without pets; and

7. The households living farther from the coast are less likely to take more vehicles that those living close to the coast.

The dissertation then presents an analysis of the households' pre-evacuation activities for hurricane evacuation based on behavioral intention data collected for Miami Beach, Florida using descriptive analysis and econometric modeling.

Descriptive analysis offers insights into activity types of the tours, travel mode, and scheduling and activity locations in terms of travel distance from home and between tour stops. It shows that shopping accounts for the dominant proportion of preparation activities. The specific items reported include food, gasoline, medicine, and withdrawal of cash, which underscores the importance of steady supply of these items. In terms of tour making behavior, most households would make a single tour, but multiple tours are observed. More than 90% of the tours are conducted by driving, which highlights the necessity of including these activities into the evacuation demand modeling. The tours' action days indicate that households perform their preparation activities early. More than 75% of the households who would make multiple tours perform the second tour on the same day of or the day following their first tour. Households would generally make the tours during daylight. About 10% of the households chain their single activity chains with their ultimate evacuation trips. The activity locations are fairly close to respondents' homes though households generally travel farther for supplies and picking-up activities. The close distance between the first and second stops suggests that the stops are generally close together, which can be used for location choice in activity generation and scheduling.

Econometric models then identify the contributing factors to the out-of-home activity participation choice and the action day choice of the first tour. The participation in the activities that involve travel is investigated via a binary logit model. Households with college graduates, larger households, and households who drive their own vehicles are more likely to engage in activities that require travel. The number of people older than 64 has a negative impact upon engaging in out-of-home activities. The action day for the first tour is examined using the discrete-time hazard-based survival model and is statistically significantly related to the activity type, household's selected evacuation time, and the number of tours. If the first tour involves purchasing medicine, the households are more likely to buy medicine early possibly due to concerns about limited supplies. If the households pick up relatives/friends in the first tour, they are more likely to conduct the tour late. Households who evacuate late are more likely to conduct their pre-evacuation activities late. Finally, households with multiple tours tend to make their first tour early.

The dissertation then integrates the behavioral findings and models into an agent-based travel demand model system for hurricane evacuation simulation, which is capable of generating comprehensive activity-travel plans for households. The system implements econometric and statistical models that represent travel and decision-making behavior throughout the evacuation process, and is flexible enough to adopt alternative behavioral models. It generates the predicted activity-travel patterns for all households in the simulation sample. Traffic assignment methods can be applied to determine traffic patterns on the network. The model system possesses the following major strengths:

- Unlike most previous models, this system explicitly captures the shadow evacuation population and produces the percentage of shadow evacuation demand close to that reported in existing studies.
- The model system reproduces the desired temporal pattern for the evacuation departures and links the departure time choice with household characteristics.
- The model system is the first to explicitly capture the pre-evacuation preparation activities via the generation-scheduling paradigm.
- The simulation mechanism of the model system recognizes taste variation and ensures that the chosen outcome is not identical for all observationally similar decision makers.

A demonstration predicts activity-travel patterns using model parameters estimated for the Miami-Dade area. The simulation results indicate the model system produced the distribution of choice patterns that is consistent with sample observations and existing literature. The model system is also able to identify the proportion of the shadow evacuation population and their geographical extent. Specifically, approximately 23% of the population outside the designated evacuation zone would evacuate, which echoes the findings in previous studies. The shadow evacuation demand is mainly located within 5 km (3.11 miles) from the coastline

7.2 ENGINEERING SIGNIFICANCE, CONTRIBUTIONS AND LIMITATIONS

This dissertation contributes to the fields of evacuation modeling and transportation engineering.

- The dissertation is among the first to develop the evacuate-stay choice model using the random-coefficient binary logit specification. It includes households' distance to the coast into the heterogeneous mean of the random parameter across households to capture shadow evacuation. Combined with the distance sensitivity factor, the model is capable of deriving different shadow-evacuation levels which can be used by an emergency management agency to evaluate different evacuation scenarios thus facilitating the devising an evacuation plan that considers the additional demand due to the shadow evacuation phenomenon.
- This study is the first to statistically investigate the evacuees' vehicle usage choice with explicit consideration given to the vehicle ownership constraint. In addition, a simulation method to generate the individual vehicle usage predictions is proposed. Improving the existing studies which mainly rely upon sample observations, it helps to facilitate a more accurate translation of household evacuation demand to vehicle travel demand. One limitation is that the vehicles usage choice model does not consider the vehicle types such as trailers and SUVs. It is helpful to estimate the quantity of these vehicles because the trailers occupy more space and usually travel slowly and may increase congestion on the evacuation routes. Accurate estimates of the number

of trailers that are likely to be taken are helpful to emergency management to devise a traffic management plan to facilitate the evacuation traffic.

- The dissertation is among the first to provide insights into households' pre-evacuation activity travel using an activity-based approach. Based on behavioral intention data collected for Miami Beach, Florida, this dissertation presents a descriptive analysis of and econometric models for households' pre-evacuation activities. It investigates the transportation aspects of activity generation and scheduling (number of tours, tour timing etc.). In addition, it bears emergency preparation implications. The descriptive analysis shows that shopping - particularly food, gasoline, medicine, and cash withdrawal - accounts for the majority of preparation activities, highlighting the importance of maintaining a supply of these items. These findings can offer better understanding of the travel derived from pre-evacuation preparations and thus enhance the accuracy of the demand representation. One limitation lies in the lack of complete activity travel information throughout the evacuation cycle. It would be helpful to examine the responsibility sharing among household members if such data are available.
- The simulation mechanism of the model system recognizes the stochastic nature of the households and ensures that the simulated outcome for a particular model component is not identical for all observationally similar households, which is a major distinction from the simulation models using a deterministic decision-maker matching algorithm such as the demand module in TRANSIMS for regular planning (Ley, 2009).
- The agent-based travel demand model system is capable of generating activity plans that works with agent-based traffic simulation tools as evidenced by the ongoing effort of applying dynamic traffic assignment to determine travel demand patterns on the Miami-Dade network and conventional trip-based simulation tools. It will facilitate hurricane evacuation management.

7.3 FUTURE DIRECTIONS

In addition to the future directions identified in previous chapters, there are other directions that can be explored. For the evacuate/stay decision, one possible direction is to investigate other important dimensions of the evacuation behavioral modeling such as the evacuation destination choice and departure timing jointly with the random parameter logit model for evacuate/stay decision. Such an effort may be challenging due to the difficulty of model estimation.

After the integration of the demand model system with an agent-based traffic simulation tool, another interesting and important application of the agent-based evacuation model system is to investigate how to facilitate the travel of emergency management personnel using agent-based modeling and simulation with the aim of improving humanitarian and disaster mitigation efforts to enhance the resiliency and sustainability of communities facing environmental challenges. This will contribute to a comprehensive abstraction of all the participants in the evacuation process. In addition, with relevant data, it is also important to examine the responsibility sharing between household members during their pre-evacuation mobilization.

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